Designing a Freight-Centric Integrated Passenger-Freight Transportation System with Routing and Bin-Packing Constraints

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Designing a Freight-Centric Integrated Passenger-Freight Transportation System with Routing and Bin-Packing Constraints

by

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Abstract

With the rapid growth of urban freight demand driven by e-commerce and same-day delivery requirements, city logistics is facing unprecedented challenges including severe traffic congestion, fragmented delivery networks, and increasing environmental concerns. In traditional transport systems, freight transport and passenger transport are mostly operated separately, especially for the road transport system and the rail transport system, resulting in underutilized capacity and redundant trips. In response to these issues, this thesis proposes a novel operational concept called the autonomous, door-to-door, multimodal collaborative "PODs" system, which aims to better integrate road and rail transport while optimizing cargo handling and routing efficiency.

This research develops a comprehensive mathematical model for a pickup-and-delivery vehicle routing problem (PDVRP) that incorporates 3-dimensional bin packing constraints with cargo compatibility considerations (3D-BPCC). The model also explicitly accounts for the transfer interfaces between road and rail modes, reflecting the practical limitations and opportunities of multimodal urban freight operations. By addressing these aspects simultaneously, the proposed model aims to bridge the gap between theoretical routing optimization and real-world logistics practices.

Four major innovations distinguish this work from existing studies. First, the model includes the handling capacity of train stations as a key constraint, which directly influences feasible routing decisions and helps avoid unrealistic transfer flows. Second, the cargo compatibility issue is included within the bin packing problem, ensuring that incompatible goods are not placed together, which improves safety and loading efficiency. Third, a sequential solution approach is adopted, solving the routing problem and the bin packing problem iteratively to reduce computational complexity while maintaining result reliability. Fourth, a systematic benchmarking analysis compares the PODs system to two traditional systems that separate freight and passenger flows, highlighting the economic and operational benefits of the integrated approach.

The model is implemented using the Gurobi optimization solver and tested on a representative dataset derived from real-world urban freight scenarios, involving multiple cargo types, nodes, and time constraints. A series of sensitivity analyses are conducted to examine how variations in penalty coefficients, such as travel distance and handling costs, affect routing outcomes and system performance. The results demonstrate that the PODs system consistently achieves lower total costs than the benchmark systems across a wide range of parameter settings. In particular, the system's advantage is primarily attributed to significant reductions in total travel distance and more efficient use of available transport capacities.

In conclusion, this thesis provides a solid mathematical foundation and practical insights for designing and operating collaborative multimodal urban freight systems. By demonstrating the cost and environmental benefits of the PODs concept, this research contributes to the ongoing efforts to make urban logistics more sustainable, flexible, and resilient. Future work could expand the model to incorporate dynamic re-routing with real-time data, stochastic demand scenarios, and the integration of emerging technologies such as autonomous vehicles and smart loading equipment.

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1 Introduction

1.1. Background introduction

Environmental problems caused by freight and passenger transportation have long been an extensively posing threat. According to United Nations (UN)[1], in 2021 around 23% of total greenhouse gas (GHG) emissions across the world originates from road passenger and freight transport, while road transport also consists of 76% of overall transport emission in EU region[2], this figure shows conflicts with EU's target in environment aspect stated in European Green Deal: a net-zero carbon emission by the year 2050.

To address this problem, the EU is advocating a mode shift process in the transportation realm. In the conceptual design phase of new transportation means, some critical operational issues are faced by the designers.

For passenger transportation, the occupancy rate of current fixed schedules of public transport in industrialized countries is rather low. For cargo transportation, the booming of e-commerce necessitates more freight delivery services within urban areas, while this would lead to a worse situation in terms of congestion and pollution. What's more, although the EU is not suffering from an immediate long-haul truck driver shortage problem as what is happening in the United States, a foreseeable driver shortage would still happen due to the retirement of a relatively large portion of bus, coach, truck and train drivers in next decade while there are not enough apprentice workers in the same industry[3].

Various transportation solutions have been explored in order to tackle these challenges. Amongst all the early exploration by transport solution providers, a novel transport system that contains the following features: automation, on-demand transport, integrated freight-passenger transportation, multimodality and co-modality is fairly reasonable. Moreover, as a large portion of long-haul maritime and road transportation demand is filled by containers, the huge success and the convenience for loading and unloading provided by the standardized, modular system are not to be neglected.

Based on these existing solutions and the knowledge learned, an assumption could be made that a system which could consolidate the freight and passenger demand altogether, a novel transportation system of which compatible the all the features above could potentially enhance the efficiency of the transportation system, and a modular vehicle system would be a good answer which provides solution to most features demanded.

According to the conceptual framework designed based on the demand proposed by the industry, and also to draw solutions to mitigate the challenges above, an automated modular collaborative transport equipment which could operate in different infrastructure systems could potentially enhance the efficiency of existing transport solution and could be a good answer which provides solution to most of the features demanded.

Given the knowledge provided by the predecessors, currently there are several companies (Rinspeed[4], Renault[5], Mercedes[6], etc.) providing such modular vehicle system solution. On the other hand, the public transit system in many cities all over the world is devoted to deeper and deeper electrification, this proves that electrification is an inevitable and irreversible trend. Based on the requirements proposed above, a transportation system which consists the character of standardized carriers, combining passenger and cargo transportation together, with carriages could be operated on both rail and road, providing flexibility in transportation capacity for both passenger and cargo and a capability of providing door-to-door service could be a decent system to address the problems stated above.

Modular design principles have emerged as a pivotal paradigm in the automotive industry, offering a myriad of benefits for both passenger and freight vehicles. This paper presents a thorough examination of the necessity and superiority of modular passenger and freight vehicles, focusing on their flexibility, resource optimization, environmental sustainability, adaptability to future technological developments, and cost-effectiveness.

To achieve the target of efficient operation of such a futuristic and potential system, optimization of route planning, minimizing empty cargo spaces, and other modular-based enhancements contribute to a more cost-effective and streamlined transportation system is fundamental process. Amongst the aspects just stated, this thesis would mainly focus on throwing light on the following unexplored context: A pickup and delivery vehicle routing problem (PDVRP, or VRP-SPD) combined with multimodal transport context (but only focus on intermodal), integrated passenger-freight transport and heterogeneous demand consolidation of modular vehicles. The author hopes the research results will not only be helpful in giving insights on the specific aforementioned pod transit system, but also provide a solid basis for the construction of a modular vehicle system, including supporting infrastructure and service network design.

1.2. Research scope and contribution

This thesis aims at the following research question:

"How can we design a mathematical optimization model to optimize the operational performance of a passenger-freight integrated, 3-dimensional multimodal modular transport system?"

To facilitate the formulation of the research plan, the research question could be further disassembled into several small sub-questions:

1. What are the objectives we aim at by optimizing the system mentioned above?
2. Which operational research (OR) models could be the basis of this holistic model?
3. How can such a complicated model be solved effectively?
4. What performance indicators should be applied in the model to measure the operational efficiency of the system?
5. How do intermodality and other distinctive features exert their impact on operational efficiency?

The scope of this research is limited to establishing a theoretical model for simulating and optimizing the operation of the pod system aforementioned on the roadside of a multimodal transport network. Furthermore, this work aims to apply the formulated model to a real-case scenario and evaluate the sensitivity of different penalty coefficients.

The main contribution of this thesis project falls in the following sections:

1. Combining PDVRP with a bin packing problem considering compatibility issue of cargo. These two parts will act as the core of the model established in this thesis, it is closer to a realistic freight-passenger combined transport scenario and thus will provide more valuable insight into the system's operation strategy.
2. Introducing the interface between road transport and railway transport. Considering that the PODs system will eventually operate on both road and railway networks, regardless of whether applying detachable carrier or not, and respect train station handling capacity will contribute greatly to the efficiency of such a system. Incorporating train station capacity into the model is of great necessity.

1.3. Thesis Outline

This thesis is divided into 5 chapters. The first chapter begins with an introduction to the background and the source of inspiration for this project, including the characteristics of the targeted transport system design. The second chapter provides a broad and thorough review of the literature regarding different aspects that are studied in this thesis, then provides the conclusion conducted by precedent scholars, what has been discussed in relevant areas and what hasn't, and finally introduces the research gap that will be filled by this thesis.

Chapter 3 first provides a general description of the context in which the model is based, then introduces the model established for addressing the research question. The first model of which the core is a vehicle routing problem with the pick-up and delivery process (PDVRP), while the second model is a 3-dimensional bin packing problem considering cargo (freight and passenger) compatibility (3D-BPCC) constraints.

Chapter 4 mainly records the experiment settings and the results provided by these experiments. A series of sensitivity analyses are carried out around different parameters, with how different components in the objective function change, a comparison between PODs system and two traditional transport systems, and what these results imply on how the system should be operated in the real world are discussed.

Chapter 5 is the final chapter of this thesis. This chapter begins by outlining the conclusion, restating the contents of each chapter, and then offers a brief conclusion regarding the case study conducted in Chapter 4. Following this, the limitations of the model and the less satisfactory aspects of the implementation are discussed, along with proposed improvements for each limitation.

2

Literature Review

The theoretical model which would be applied in this thesis, as introduced in Chapter 3, is a specialized version of the pickup-and-delivery vehicle routing problem (PDVRP). The original (VRP) is a crucial problem in the fields of operations research and combinatorial optimization, involving the efficient allocation of a fleet of vehicles starting and terminating the service trips at a depot to service a set of customers. This problem was first stated by Dantzig and Ramser in 1959[7] and has been explored by many scholars with many variants and extensions. In this section, a discussion on recent trends and those which are most relevant to the model established in the previous chapter will be elaborated.

As for the pickup-and-delivery problem (PDP), it was first introduced by Desrochers et al.[8] and Savelsbergh and Sol[9]. PDP could also be categorized as a variant of VRP, as defined by the latter. In a general PDP, the vehicles are not necessarily serving demand from the depot, but could also pick up any order along the route as long as the constraints are not breached. Speaking of constraints, PDP typically contains time window constraints, vehicle capacity constraints and multiple depots, and all these features are included in the model in Chapter 3. The main distinctive feature of our model is the integration of passenger and freight transport in a modular multimodal transport system, together with the platooning of modular vehicles and considering heterogeneous demand consolidation and synchronization of railway schedules. These specific characteristics have been individually researched, as will be discussed in the following parts of this chapter, but their combination has yet to be explored.

For the core part of the model, although there is no identical background setup, several existing operational research problem categories are similar to our context, which indeed gave us inspiration for detailed model construction.

There are several OR problems similar to a classic PDVRP, including container drayage problem (CDP), as the pods could be seen as the container without trailer, and there are several existing literature examined this problem with multiple merit algorithms[10][11][12], but since it contains no intermodality consideration, this problem doesn't suit our case quite well, but we nevertheless could be inspired from these works.

In a sense, DARP (dial-a-ride problem) could also be regarded as a similar question to what we set to explore in this thesis, as DARP consists of the decision on routing as well as the scheduling for pick-up and delivery[13]. Based on this classical problem, Li et al. proposed a novel operational research question which they named SARP (share-a-ride problem) in 2014[14], in which freight and passengers share the capacity of a same taxi in the original context. This could also be seen as a basis for the problem this thesis would like to explore, but SARP also lacks the critical part of taking the interface between transport modalities into consideration.

2.1. Vehicle Routing Problem

2.1.1. Routing problem in multimodal, integrated passenger-freight transport

This is the most researched section for all the variants of PDVRP, varieties of models, and corresponding algorithms are proposed over studies carried out in past decades. PDVRP in the multimodal transport section is highly based on the basic model, by adding multiple constraints, the model can adapt to different detailed contexts easily, according to its high compatibility and extensive nature.

Research in this section also has multiple focal points due to the differences in the researchers' professions. Most recent work carried out in this area focuses on algorithm optimization, while the minorities have concentrated on facility location planning, service network planning, network resilience analysis, etc.

The number of studies on PDP with a multimodal background has ushered in rapid growth since 2012, most of the relevant literature in the early years didn't introduce the modal of freight-sharing carriage capacity with passengers but only share infrastructure. In the context of this project, we not only aim at carriers sharing the same infrastructure system but also passengers and freight sharing the same capacity in a carrier. Although the number of studies related to the integration of passenger and freight transportation increased after it was proposed, when we scope down to those who have introduced a passenger-freight integrated transport system with a multimodal background, the number of literature is rather few, and as for those literature which discussed the interface between different modalities is even less.

Although the total number of relevant literature is few, multiple interesting literature still provided insight on integrated passenger and freight transport published in recent decades, most of which are urban scenario-based, while some of them included the combination with railway transport (including long haul railway service and subway)[15][16][17][18][19][20].

Generally, the vast majority of these studies are dedicated to the combination of passenger and freight transport in existing urban PT systems, for example, subway and bus networks. Some scholars have put relentless effort into this area for a long time. Ghilas et al.[21] studied the opportunity to use the available public transportation network to perform freight transportation, operating according to predetermined routes and schedules to minimize the total operating costs. They consider that part of the requests' journey can be performed by a passenger transportation service, synchronizing it with dedicated Pick-up and Delivery (PD) vehicles. Later, Ghilas and his colleagues further extended the previous work by applying delivery time windows for the PD in 2016[22] and 2018[23]. This series of research, finished by Ghilas and fellows, provided some exquisite techniques for solving a PDP with time windows and scheduled line (PDPTW-SL), but the critical point between the existing research and our context is that our system will be operated without a basic service network (e.g., bus service network).

The research with the most similar background to this project is the one conducted by Li et al.[24], this research extended the application scenario of research conducted by Ghilas et al. and Masson et al. to a transport system with multimodal background, it discussed the dynamic passenger flow constraints and the scheduled line operation constraints, but the road segment services in this research are provided by dedicated freight vehicles, on the contrary, the transport system to be researched in this project will provide a comprehensive freight-passenger transport service all across the network.

As stated before, research in this section is thorough and detailed, yet there are only very few studies infusing modular vehicles in PDVRP. This is mainly because modular vehicle is a new feature binding with multimodal transport. Even if the scope of this thesis project is not to look into the detailed operation of this system, we will nevertheless take the interface between road and rail segments into consideration. This would be one of the main research gaps to be filled and an innovative point of this thesis.

2.1.2. Routing problem for modular vehicles

The projects regarding modern modular vehicles haven't been proposed much until the year 2015, but there are varieties of modular vehicle projects in progress by different research entities, technology companies and car manufacturers, and these projects feature in different areas, for example, the Pop.Up Next designed by Airbus featured in drones, the Snap/microSNAP project proposed by Rinspeed could change carriages with different functions in different sizes, while there are similar projects ongoing within large companies such as Mercedes-Benz (vision urbanetic) and Renault (EZ-PRO). There are also multi-functional urban commuting vehicles like CityCar designed by a research group from MIT. But generally, these modular vehicle projects are still in early design phases, most of which are mere conceptual models, thus the research in this section is quite few.

Current research in this section mainly focuses on carrying out feasibility analysis of such systems[25][26]: whether they're really helpful in mitigating city congestion, or they could provide better solutions towards the PT system, etc. What needs to be mentioned is that these systems generally feature function-specified carriages, which means in these projects cargo carriers and passenger carriers are not equipped on a same chassis at the same time, which also means they don't support cooperative transport for now, while in this project, passengers and freight cargo co-exist in a same carriage, which is a rarely explored research area.

Despite the limited number of studies conducted in this area, we would like to mention several studies regarding the routing problem of modular vehicles, and the number of relevant studies is growing steadily. Pei et al.[27] introduced a passenger transport system with multiple modules which could form a platoon. They then formulated a mixed integer non-linear model to optimize the routing of the pods in a small-scale testing network and found a noticeable reduction in overall cost compared to a traditional shuttle bus system. This research is a pioneering research conducted in this area, but it doesn't include the feature of collaborative transport of passenger and freight demand, while it also didn't take intermodality into consideration. Speaking of intermodality, Lin et al.[28] proposed a system with two transport modalities that integrated passenger and freight transport, the vehicles could also be merged into platoons and split whenever needed. The authors suggested the high potential of modular, integrated transport systems regarding their efficiency, but their discussion is much too qualitative and lacks support for quantitative analysis or any real cases.

Liu et al.[29] designed a novel operational flexible autonomous transit system dedicated to passengers, and they designed a 2-stage joint optimization model to optimize routing and scheduling problems simultaneously. The research results indicated that this system has better service quality and operational cost than conventional bus systems.

Zhang et al.[30] utilized the advantage of modular transit to cover the first- and last-mile problem and low occupancy rate in off-peak hours which has always been a problem for conventional bus and metro systems, they mathematically modeled the system in a time-expanded network and aimed at maximize service rate, by comparing the KPI with a door-to-door shuttle service, they proved the supremacy of modular transit system.
Although the literature reviewed above, together with some unlisted research[31], perfectly stated the superiority of modular transit systems compared with conventional public transit, they are all dedicated to the passenger transport system and lack research on heterogeneous demand consolidation.

2.2. Demand consolidation and compatibility

The growth and increasingly fragmented demand for urban logistics services burden urban transportation networks with increased volume and a higher level of pick-up and delivery complexity, calling for tighter coordination and consolidation of shipments. The heterogeneous demand consolidation problem originates from the demand for solutions for two different problems. The first one is the demand for finding a maximum utilization rate for cargo carrier capacity, the other one is transportation risk management, which mainly focuses on freight flow management, isolating hazardous materials according to their characteristics.

In the context of this project, the main focal point is the former one and there are some recent researches incorporates heterogeneous demand consolidation. An early example of relevant research is conducted by Bortfeldt and Homberger in 2013[32]. In this article, they proposed a two-stage metaheuristic algorithm to solve the vehicle routing and loading problem (VRLP) by first solving the loading problem, then solving the routing problem. This research laid a solid basis for future research in this area. The paper written by Meliani et al.[33] studied a particular integration of the heterogeneous fleet vehicle routing problem with 3-dimensional loading constraints (3L-HFVRP) and provided good solution to 76% of tested cases with a variant of tabu searching (TS) algorithm. Regarding demand consolidation in the VRP context, there is a certain variant of VRP integrated shipment consolidation feature researched by Cortes and Suzuki[34], called VRPC. They proposed this model based on the classical VRP with split delivery (VRPSD) and proved with a real case study that VRPC could match or outperform VRPSD by 10% in terms of total travel distance and could improve the efficiency of first- and last-mile delivery. A huge limitation of this article is that the model proposed by Cortes and Suzuki only discussed the feasibility of freight consolidation and the simple transshipment for consolidation, but it has nothing to do with traditional BPP. Nevertheless, this research is one of the rare ones considering freight demand consolidation at the departure node, while in most of the existing literature, shipment consolidation is only considered in median nodes including cross-docks[35][36][37][38] or consolidation/distribution center[39] in the network. A note-worthy point is that the study conducted by Ji et al. is the only one in this category which combined a 2-dimensional BPP with a routing problem and cross-dock transshipment/consolidation possibility.

Another interesting research was carried out by Liu and Zhao in 2019[40], in which they proposed a mixed integer programming model combining cargo consolidation with routing decisions to minimize one-time costs for selecting the subset of vehicles and total operation costs. This model is based on their cargo flow prediction model developed based on the traffic assignment 4-stage model. But this research, together with the one conducted by Cortes and Suzuki, both neglected the possibility that there's always a compatibility problem between different kinds of cargo, which is the main gap we would like to fill in this area by this thesis.

The literature reviewed above all neglected the fact that in real-life operations, some cargo can't be put together. To address this limitation, another branch of BPP with special constraints considering the compatibility of cargo appeared. Santos et al.[41], for example, first proposed the bin packing problem with compatible categories (BPCC) and efficiently solved it with a variable neighborhood search (VNS) algorithm. The latest research in this area, conducted by Tsao et al.[42], designed three different metaheuristic algorithms to solve a 3-dimensional bin packing problem considering incompatible products. These studies are more algorithm-based, plus, although they provided valuable insight on the modeling of bin packing problems with compatible categories, they haven't taken the routing problem into consideration. In this thesis, we would like to put the two different aspects of the model together and provide a good solution to VRLP with compatible constraints (VRLPCC).

An overview table of some most relevant literature regarding the vehicle routing section for this thesis is presented in the following Table 2.1. Another table containing the contents of vehicle capacity usage optimization is demonstrated as Table 2.2.

Table 2.1: literature Overview-1

Literature	Operations	Demand	Objective	PD	VRP	Modular vehicle	Multimodal	Schedule synchronization
This work	Modular vehicle platoons	Passenger & Freight	Min. total travel time & Max. capacity utilization rate	✓	✓	✓	✓	✓
Masson et al. (2013)	PD with transfers	Freight	Min. travel distance	✓				
Chen and Li (2021)	Modular autonomous vehicles	Passenger	Min. passenger waiting time and total operational cost	✓				
Hatzenbühler et al. (2023)	Modular vehicle platoons	Passenger & Freight	Min. n.o. vehicles in operation, passenger travel time cost and unserved demand	✓	✓			
Sitek et al. (2021)	PD with capacitated customers and alternative destination	Freight	Min. travel distance	✓	✓			
Shi et al. (2020)	unpaired PD, multi vehicles	Freight	Min. total transportation cost	✓	✓			
You et al. (2023)	LCDP with truck platooning	Freight	Min. cost under feasible schedule	✓	✓			
You et al. (2020)	LCDP with truck platooning	Freight	Min. total cost	✓	✓			
Li et al. (2014)(2015)	SARP	Passenger & Freight	Min. total cost and extra travel time	✓	✓			
Ghilas et al. (2014)(2016)(2018)	PD with scheduled bus service	Passenger & Freight	Min. operational cost of PD vehicle and using scheduled lines	✓			✓	✓
Masson et al. (2017)	PD in 2-tier multimodal distribution network	Passenger & Freight	Min. generalized total route cost	✓			✓	✓
Li et al. (2021)	PDVRP in a multimodal transport network considering dynamic capacity constraints	Passenger & Freight	Min. total transport time at station hubs	✓			✓	
Pei et al. (2021)	Modular vehicle platoon formulation	Passenger	Min. n.o. Vehicles in operation and passenger travel time	✓		✓		✓
Liu et al. (2021)	VRP and scheduling of modular PT system	Passenger	Min. operational cost & max. service quality	✓		✓		

Table 2.2: literature Overview-2

Literature	Operation	Modality	Objective	PD	VRP	Compatibility
Bortfeldt et al. (2013)	VRLP	Single	Min. n.o. routes and total travel distances		✓	
Meliani et al. (2022)	VRLP	Single	Min. n.o. vehicles and total cost of each route		✓	
Tsao et al. (2024)	Multiple BPP	-	Min. n.o. bins			✓
Santos et al. (2019)	BPP	-	Min. n.o. bins			✓
Cortes and Suzuki (2020)	VRPC	Single	Min. total travel distance		✓	
Ancele et al. (2021)	PDVRP with consolidation	Single	Min. total driving time	✓	✓	
Ji et al. (2022)	Many-to-many VRP with 2-d loading constraints and consolidation	Single	Min. total travel cost and operation cost		✓	✓

Through the tables, we could find that the least attached feature to a PDVRP is the heterogeneity of the time window for different types of nodes, as none of the existing research in relevant areas draws attention to this feature. Another aspect which hasn't been thoroughly explored is the synchronization with the PT operation schedule, although Pei et al.[27] included the consideration of the PT system schedule as the context of this research is a futuristic PT system. Lastly, to the best of my current knowledge, there hasn't been any precedent literature listing the maximization of single-vehicle capacity usage combined with a preset cargo priority, mostly the objective will be set as a minimum number of used vehicles.

2.3. Algorithms for solving VRP and its variants

Vehicle Routing Problems (VRP), as well as another question that will be discussed in this research, the bin-packing problem (BPP), have both been proven as NP-hard problems mathematically, which means it is impossible to obtain an exact solution to these problems in polynomial time. Given the high computing complexity of VRPs, there are several exact algorithms to provide solutions to the general VRPs, as well as another element in the model to be proposed in chapter 3: the pickup and delivery problems (PDP). Many scientists carried out research on this specific topic, especially during the early years when meta-heuristics were not proposed. An early literature review on solving VRP with an exact algorithm was published by Laporte and Norbert[43] in 1987. In 1991, Dumas[44] proposed an exact algorithm for PDP with time windows. This algorithm used a column generation method to solve problems with path constraints and was capable of handling multiple sites and different types of vehicles. This study laid the foundation for subsequent solution methods for PDP problems. Different branches of exact solving methods have been explored in depth ever since, including the Lagrange-relaxation-based method, column generation method and dynamic programming (for details see [45]). Until now, solving VRPs with an exact algorithm is still a hot topic especially for the algorithm optimization experts, as a showcase of their talent.

However these exact solving methods have been optimized in the past half century, the drawback of finding an exact solution to VRP or PDPs is still inevitable: the process of these algorithms solving NP-hard problems with large problem instances is not only extensively time-consuming but also requires a huge amount of computing resources, which is generally not acceptable for most of the cases. As an alternative, meta-heuristics algorithms were proposed to give approximate solution to these kind of questions in a more reasonable timespan. With the development since the mid-1960s, these algorithms could provide solutions almost as good as those provided by exact methods.

The very first meta-heuristics algorithm proposed for solving VRP traces all the way back to 1964, when Clarke and Wright[46] provided a concept of "savings". The main idea of this "saving algorithm" is to merge customer routes to reduce the total travel distance, thereby minimizing the total cost while meeting the necessary demands and constraints. This research ensemble the start of the metaheuristics algorithm's application in solving routing problems, while the core part of it still serves as an operator in the newly developed neighbourhood searching (NS) family.

As the 21st century began, researchers studying routing problems started to adopt more sophisticated metaheuristic approaches. For example, Nanry and Barnes (2000)[47] introduced a reactive tabu search method that successfully addressed the PDP problem by employing multiple neighborhood structures. Around the same time, Li and Lim (2001)[48] proposed a hybrid algorithm that combined simulated annealing with tabu search, proving particularly effective for large-scale multi-vehicle PDPs. Their work, along with the benchmark instances they developed, has since become a standard reference for evaluating the performance of new algorithms designed for general PDPs. Another notable contribution is the two-stage method by Bent and Van Hentenryck (2006)[49], which applied simulated annealing in the first stage to reduce the number of routes and then used large neighborhood search in the second stage to minimize travel costs.

In 2007, Pisinger and Ropke[50] demonstrated that the Adaptive Large Neighborhood Search (ALNS) framework could be applied to five different variants of the vehicle routing problem, reformulating them into PDPTW instances. ALNS builds on the neighborhood search strategy originally introduced by Paul Shaw[51], but extends it by modifying a large set of variables at each iteration. Within this framework, solutions are iteratively destroyed and reconstructed using heuristic operators. Fleszar et al.[52] later developed a Variable Neighborhood Search (VNS) algorithm for the Open VRP and subsequently suggested a multi-phase oscillating VNS for VRP in general. Unlike ALNS, VNS does not rely on destruction–repair cycles to generate new solutions; instead, it explores the solution space by systematically altering neighborhood sizes. Building on this line of research, Şevkli and Güler (2017)[53] tackled a real-world newspaper distribution case modeled as an Open VRP and introduced a new multi-phase oscillating VNS algorithm, which utilized K-means clustering to generate initial solutions.

Beyond ALNS, numerous other algorithms have been applied to VRP and its many variants. One widely used approach is the Genetic Algorithm (GA), which is valued for its ability to search across vast, unstructured solution spaces and its potential for parallelization, thereby accelerating the search process[54]. Other metaheuristics frequently employed include Ant Colony Optimization (ACO)[55, 56], Simulated Annealing (SA)[57, 58], and Particle Swarm Optimization (PSO)[59, 60], among others. Despite this variety, ALNS has proven particularly effective for highly complex optimization problems where the solution space is extremely large and solution quality varies widely. This effectiveness explains why ALNS has gained increasing prominence in recent years.

2.4. Three-dimensional bin-packing problem and its solving algorithms

Bin-packing problem (BPP) is a classical NP-hard, combinatorial optimization problem [61], in which rectangles or cuboid boxes are placed within a larger rectangle/box called the container. The sides of the rectangles/boxes are parallel to one another. The most widely researched objective of this kind of question is to minimize the number of containers used for packing up all demand.

Bin-packing problems can be divided into different sub-categories by many criteria. The most widely-used standard is the dimension of items considered in the packing constraints, BPP can be divided into 1-dimensional (1D-BPP) or multi-dimensional packing problems, including 2-dimensional (2D-BPP) and 3-dimensional (3D-BPP) version, the latter sometimes is also known as the container loading problem (CLP).

The existing literature in the field of 3D-BPP examines various types of problems with different constraints and solution approaches. The basic constraints that support the model are the geometrical constraints, which means, the items to be packed in the box should be completely contained in the internal volume of the box. Apart from this, there are different kind of constraints that can be taken into discussion as well.

For the other constraints considered in these different BPP branches, weight limit constraints[62][63][64][65], packing orientation constraints[66][67][68] and stacking stability constraints[69][70][71] are the most widely considered. Sometimes there are other constraints discussed by researchers, like weight distribution constraints[72][64], load priority constraints[71][73] and allocation constraints[74][71]. These less-discussed constraints can make the models closer to real application scenarios, but some of them also significantly increase the complexity of both modeling and computing processes.

Same as other NP-hard problems, there are two main approaches for finding a solution to any specific BPP or its variants: the exact algorithms and the heuristics algorithms. Within the class of 3D-BPP, they are particularly hard to solve compared with simpler packing problems, for example, the 1-dimensional knapsack problem. Consequently, very few exact algorithms exist, and they are mostly related to mixed-integer programming[75][74][76] or dynamic programming[77] with branch-and-bound method[78]. As for the heuristics algorithms, there is more and more research conducted around this specific topic. The early heuristic algorithms proposed by the pioneers were the first-fit algorithm, the best-fit algorithm and others. Later, since the late 2000s, with the development of general metaheuristic algorithms, new solution approach for BPP started to pop up, including xxx, xxx and xxx, the proposal of these algorithms mainly improved solving time while keeping the solution's high optimality.

During recent years, with the boom in emerging concepts such as machine learning, computer scientists started to try solving BPP with deep learning or reinforcement learning since 2017[79][80], these novel techniques are especially useful in solving online bin-packing problems (a.k.a. real-time bin-packing problems), but since the online bin-packing problems are too deviated from the scope of which this thesis wishes to focus on, they will not be reviewed here in detail.

In this thesis, the research question can be answered by establishing a model combining 3D-BPP and PDVRP, which is also a segment that has received less attention. In the existing literature, the combination of BPP and VRP is sometimes known as vehicle routing and loading problems (VRLP), the first formal research about this topic was conducted by Doerner et.al. in 2007[81]. For the two-dimensional cases, a constraint programming model approach was suggested by Malapert et.al.[82]. Following the proposal of a prototype of ARLP in 2006, the research interest regarding how to solve the combined packing and routing problems has grown immensely over the past two decades. Solving algorithm-wise, the researchers not only explored different setups in local/neighbourhood searching[71][83][84][65], but also developed combinatorial heuristics algorithms[70][85][74][86][87] for solving this highly complicated question. Similar to online bin-packing problems, some current research explores the possibility of utilizing deep (reinforcement) learning as a problem-solving strategy[88]. Context-wise, more realistic scenario setups are taken into consideration as well, such as first/last-mile logistics pick-up and delivery with disruption[89].

It is note-worthy that the existing literature mostly applies a "standard" PDVRP and explores different kinds of BPP. In contrast, this thesis will introduce new features to the PDVRP section, while implementing a rather standard 3D-BPP, to better simulate the application scenario of this system.

To sum up with this section, although most of the attributes mentioned above are thoroughly researched and some studies even provide valuable insight in a cross-section manner, there are no researches combining all four sections altogether, which is also the eventual research gap we will fill after the research which would be conducted in this thesis. A huge amount of literature researched the algorithms for the two NP-hard problems (VRP and BPP), and which approach will finally be applied still needs careful scrutiny.

3

Problem statement

3.1. Problem statement

In this thesis, we aim to establish a mathematical model representing a transport system in which passengers and freight can be handled in the same infrastructure network, with the same road and transportation carrier. The load portion of the pods is variable, while the loading strategy is determined according to the objective function.

The transport system modeled in this thesis can be regarded as a variant of the pick-up and delivery problem, as is roughly demonstrated in the following Figure 3.1. The vehicles (named as pods in the following parts of the thesis) utilized in the system can be used for transporting freight cargo and passengers, the two parts can be concurrently put in the same pod as long as the cargo items do not react with one another in a potentially harmful way, or the items are suitable to be put together with passengers (i.e., cargo are not potentially harmful to passengers).

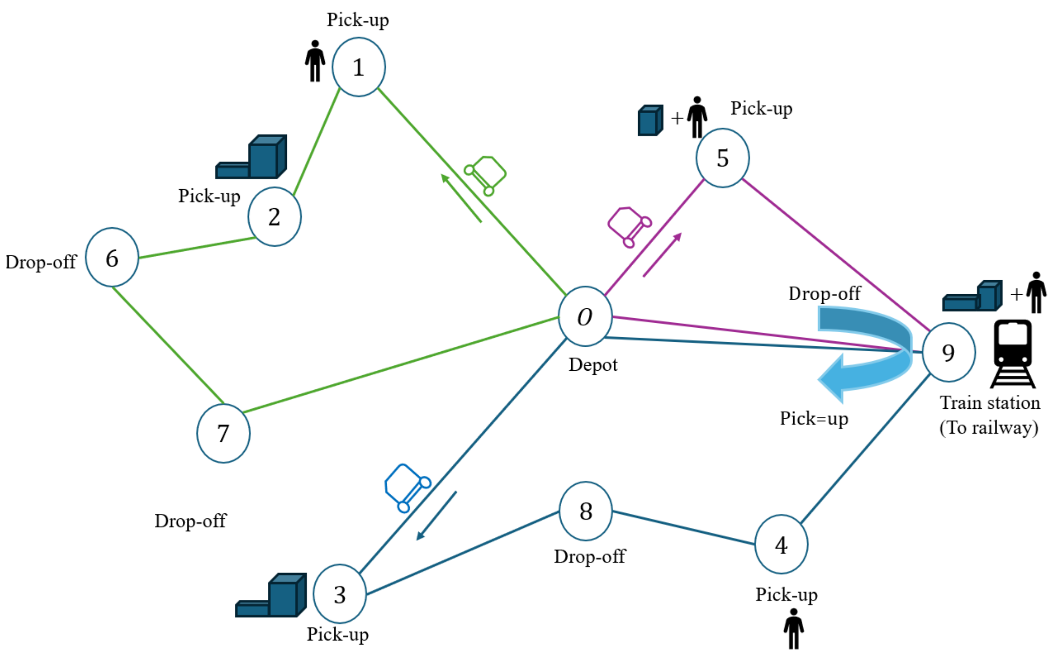

Figure 3.1: Network schematic diagram

The optimization model representing this system is composed of 2 different decision processes, which are the packing decision and the routing decision. These two decisions will be made in a sequential manner, by first solving the routing problem, then checking the feasibility of the packing problem. These two problems will be considered as one holistic optimization problem.

Models related to the decision processes are a bin-packing problem and a VRP-SPD (vehicle routing problem with simultaneous pick-up and delivery, a.k.a. PDVRP), with extra constraints contributed to a variant of each classic model. The components will be defined and described in following sections 3.3.3-3.3.4.

The PDVRP is defined on an undirected complete graph $G(N, A)$ over an operation time horizon $[0,\ T_k]$. N is the set of all nodes and is composed of four parts: the starting depot, ending depot, all pick-up nodes (P) and all drop-off nodes (D) and train stations (T), in which depots are contained by one set O.

Since this thesis project is more freight-centric, which means freight demands in the network need to be served in higher priority, differentiating different kinds of pick-up nodes is of great necessity. Thus, we further divide them into two different subsets, which are P^p and P^f, which stand for passenger pick-up node and freight pick-up node respectively.

Let V be the set of pods, for any pod $k \in V$, it should start a service trip at the starting depot and end its service at the ending depot. In the road network, a train station T exists, some of the demands in the network will be transported to the train station while the train station will generate a certain number of demands to be transported to other drop-off nodes. To distribute pick-up and delivery demand at the train station, two dummy nodes (T_d and T_p) are introduced, the former one stands for where demands transported to the train station are dropped, while the latter stands for the train station where demands at the train station are picked up. Considering that train stations have a handling capability upper bound, a capacity value for the train station is introduced. This capacity value limits the number of pods accessing the train station within a certain time interval. The pods are free to access train station nodes as long as the capacity is not exceeded, then they go back onto the road network, deliver demand picked-up at T_p, and finally end their service trip at the ending depot.

3.2. Model assumption

Before introducing the mathematical model proposed in this research, we would like to first introduce the assumptions that the following model is built on. The assumptions are listed as follows:

1. Passengers and freight are always ready for pickup at the expected arrival time.
2. Regardless of which kind of demand a node has, the pods always have the same average dwelling time.
3. The pods are regarded as homogeneous, they all have the same geometrical size, weight capacity, driving speed, etc.
4. The travel time between nodes is fixed, it solely depends on the distance between nodes and the travel speed of the pods.
5. The train station nodes have a limited capacity for the pods entering the node. This limit is measured as the number of pods accessing the node per minute, regardless of demand loads on the pods.
6. All pods start their services from the same starting depot and end their services at the same ending depot.
7. All the freight demands need to be served, while passenger demands can be skipped with a certain amount of penalty, as this system is designed to be a freight-centric system.
8. For the ease of bin-packing calculation, each demand, regardless of passenger or freight, is treated as a cuboid with a specific geometric dimension and mass.
9. All the demand at the same node to be picked up is non-splittable, which means, the demand at one pick-up node is either carried by one pod or is completely skipped.
10. The rotation scheme of how the demands are packed in the pod is not considered in this research.

These assumptions make sure that the model in the following sections can cover all the main aspects we wish to explore without making it too complicated and unsolvable.

3.3. Model formulation

3.3.1. List of notations

The notation of sets, parameters and variables are listed in Table 3.1.

Table 3.1 Sets, parameters and variables notations

Notation	Description
Indices	
i, j	Indices for nodes
k, m	Indices for pods
v, w	Indices for individual items
r, s	Indices for cargo types
Sets	
N	Set of all nodes, $N = P \cup D \cup T \cup O$
O	Set of depots, $O = O_s \cup O_e$
P	Set of all pick-up nodes, $P = P^p \cup P^f = \{1, 2, \ldots, n\}$
P^p	Set of all passenger pick-up nodes
P^f	Set of all freight pick-up nodes
P^t	Set of all pick-up nodes of which demand will be transported to train station
D	Set of all drop-off nodes, $D = \{n+1, n+2, \ldots, 2n\}$
D^t	Set of all drop-off nodes of which demand will be transported from train station
T	Set of the train station, composed of two dummy nodes T_p and T_d
I	Set of all time intervals for pods to enter train station
V	Set of all pods
J	Set of all items
J^i	Set of items set to depart from node i
Γ	Set of all cargo types
Parameters	
u	Maximum platoon length
T_k	Longest travel time per service trip per pod
α_c	The coefficient for total travel cost term in objective function
c_{ij}	Travel distance per pod on arc (i, j)
t_{ij}	Travel time on arc (i, j)
τ_i^k	Pod k's service time at node i
a^i	Expected arrival time at node i
α_p	Unit cost for skipping passenger demands
α_o^p	Unit cost for passenger demands taking detour
α_o^f	Unit cost for freight demands taking detour
α_l^p	Unit cost for pods arriving late at a passenger-related node
α_l^f	Unit cost for pods arriving late at a freight-related node
σ_v	Priority level of item v
α_k	Unit cost for deploying a pod
C_{rs}	Compatibility indicator, 1 if cargo type r and s are compatible, 0 otherwise

w_i	Width of demand at node i
d_i	Depth of demand at node i
h_i	Height of demand at node i
q_i	Weight of demand at node i
W_k	Width limit of pod k
D_k	Depth limit of pod k
H_k	Height limit of pod k
Q_k	Weight capacity of pod k
C^t	Train station capacity
ρ	Average train departure time period
M	Sufficient large positive number
Decision variables	
x_{ij}^k	1 if pod k travels on arc (i,j), 0 otherwise
s_i^p	1 if passenger pick-up node i is skipped, 0 otherwise
o_i^k	Continuous variable denoting the extra time taken for detour
e^i	Early arrival time at node i
l^i	Late arrival time at node i
B_i^k	Vehicle k's arrival time at node i, continuous
Q_i^k	Quotient part of modulo calculation, integer
C_n^k	1 if pod k arrives train station in time interval n, 0 otherwise
y_{ik}	1 if demand at node i is served by pod k, 0 otherwise
v_k	1 if pod k is deployed, 0 otherwise
f_{rk}^v	For item v belongs to cargo type r, $f_{rk}^v = 1$ if it's assigned to pod k, 0 otherwise
(X_i^k, Y_i^k, Z_i^k)	Coordinate of demand placement pivot point (left-rear-bottom point) at node i in pod k

3.3.2. Optimization object

The main objective of this model is to minimize the overall operational cost of this transport system. To reach this goal, an objective function should be proposed, and it needs to obtain the main aspects having an impact on operational cost. In this thesis, the objective function to be optimized consists of 7 terms.

The first term is the total operational cost of all pods providing transport services.

The second term denotes the penalty cost for not serving passenger transport demand, which is, the total number of skipped demand times the priority level of demand v, and this term consists of another factor α_p, which could be used for further sensitivity analysis in next stage of the project.

The third term calculates the fixed cost of deploying pods, it is the product of unit fixed cost λ_k and number of pods deployed to fulfill the demands.

The fourth to the seventh terms are related to the temporal dimension. The fourth and fifth penalty terms refer to the total penalty for taking a detour during transport services, where the detour time for passengers and freights is calculated independently. Similarly, the sixth and the seventh calculate the penalty for not serving demand requests at the expected arrival time, also known as the tardiness penalty in the upcoming chapters of this thesis.

The complete objective function is written as following Equation 3.1:

$$
\begin{aligned}
Min\ Z = & \sum_{i\in N}\sum_{j\in N}\sum_{k\in V}\alpha_c c_{ij}x_{ij}^k + \sum_{i\in P^p} s_i^p * \alpha_p * \sigma_v + \sum_k \alpha_k * v_k \\
& +\alpha_o^p \sum_{i\in P^p}\sum_{k\in V} o_i^k \\
& +\alpha_o^f \sum_{i\in P^f}\sum_{k\in V} o_i^k \\
& +\alpha_l^p \sum_{i\in P^p}\sum_{k\in V} l_i * \omega_i * \sigma_v \\
& +\alpha_l^f \sum_{i\in P^f}\sum_{k\in V} l_i * \omega_i * \sigma_v
\end{aligned}
\tag{3.1}
$$

Since the constraints imposed on the objective function can be separated into two groups— a variant of the bin-packing problem and a variant of the vehicle routing problem with pick-up and delivery (PDVRP)—these two issues, along with the corresponding model constraints, will be introduced in the following sections of this chapter.

3.3.3. Bin-packing problem

In our context, passengers will be treated as a special kind of cargo occupying a specific volume and with a specific weight. The packing problem can be described as a 3-dimensional bin packing problem considering the compatibility of cargo (3D-BPCC). Similar research around this specific topic has been carried out by [42] and [41], although these existing literature put too much focus on the bin-packing problem itself, they nevertheless laid a found basis for the model that established in this section. A rough sketch of this problem is shown in Figure 3.2:

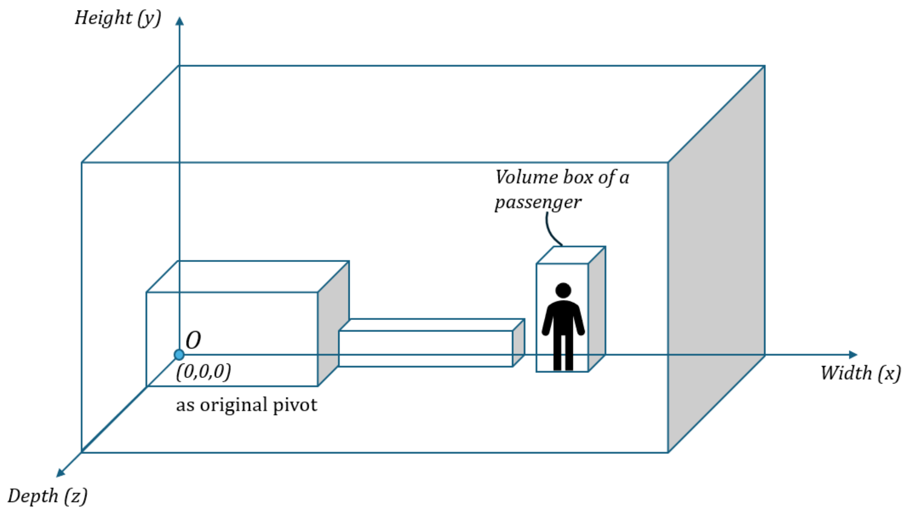

Figure 3.2: Schematic diagram of 3D-BPCC

The constraints correlated to this 3D-BPCC will be listed in the following section:

$$\sum_{k\in V} y_{ik} + s_i^p = 1 \qquad \forall i \in P^p \tag{3.2}$$

$$\sum_{k\in V} y_{ik} = 1 \qquad \forall i \in P^f \tag{3.3}$$

$$X_i^k + w_i * y_{ik} \le W_k * v_k \qquad \forall i \in P,\ k \in V \tag{3.4}$$

$$Y_i^k + h_i * y_{ik} \leq H_k * v_k \qquad \forall i \in P,\ k \in V \tag{3.5}$$

$$Z_i^k + d_i * y_{ik} \leq D_k * v_k \qquad \forall i \in P,\ k \in V \tag{3.6}$$

$$\sum_{i \in P} q_i^k \leq Q_k * v_k \qquad \forall k \in V \tag{3.7}$$

$$\sum_{i \in P} y_{ik} \leq M * f_{rk}^v \qquad \forall r \in \Gamma,\ k \in V,\ v \in J^i \tag{3.8}$$

$$f_{rk}^v + f_{sk}^v \leq 1 \qquad \forall r, s \in \Gamma,\ \ v \in J^i,\ k \in V,\ C_{rs} = 0 \tag{3.9}$$

$$X_i^k + w_i \leq X_j^k + M\left(1 - y_{ik}\right) + M\left(1 - y_{jk}\right) \quad \forall i, j \in P,\ i {\leq} j,\ k \in V \tag{3.10}$$

$$Y_i^k + h_i \leq Y_j^k + M\left(1 - y_{ik}\right) + M\left(1 - y_{jk}\right) \quad \forall i, j \in P,\ i {\leq} j,\ k \in V \tag{3.11}$$

$$Z_i^k + d_i \leq Z_j^k + M\left(1 - y_{ik}\right) + M\left(1 - y_{jk}\right) \quad \forall i, j \in P,\ i {\leq} j,\ k \in V \tag{3.12}$$

$$y_{ik} \leq q_i^k \qquad \forall i \in P,\ k \in V \tag{3.13}$$

The constraints are explained as follows:

Constraints (3.2) and (3.3) ensure every demand node i is either served by exactly one pod k or skipped, more specifically, passenger demands can be skipped while freight demands are not to be skipped. Constraints (3.4)-(3.6) measure the geometrical constraints in another manner, which is, given the pivot coordinate of placement position, the cargo to be loaded at node i should be kept within the box. Constraint (3.7) states that the weight of loaded items in pod k should not exceed the weight capacity limit of the pod. Constraints (3.8) and (3.9) discussed the compatibility problem, which is, that two items belonging to incompatible cargo categories should not be transported by the same pod.

Constraints (3.10) - (3.12) are the non-overlapping constraints, they restrict two items (v and w) which are transported by the same pod k cannot overlap one another on every projection plane (xOy, yOz, xOz). At least one of these three constraints should be valid to fulfill the non-overlapping requirement. What also needs to be mentioned is that in this research for the sake of simplicity, we only consider one orientation for cargo loading.

Constraint (3.13) restricts the relationship between q_i^k and y_{ik}. When demand at node i is set to be transported by pod k, q_i^k should be greater than 0, otherwise there are no demands depart from node i and q_i^k should be 0.

Last but not the least, the load of each pod at both start and end depot should be 0:

$$q_0^k = q_{2n+1}^k = 0 \qquad \forall k \in V \tag{3.14}$$

3.3.4. Routing problem

One core problem to be researched by this thesis is the routing problem of pods. Routing decisions to be made by these de-centralized, automated pods can be seen as a variant of PDVRP, as stated at the beginning of this chapter. The constraints in this section are composed of 3 groups of constraints, namely routing constraints, time-window constraints and platooning constraints. These constraints will be introduced in detail in the following subsections.

Routing constraints

In this subsection, flow and routing-related constraints are listed:

$$\sum_{j \in N} \sum_{k \in V} x_{ij}^k + s_i^p = 1 \qquad \forall i \in P^p \tag{3.15}$$

$$\sum_{j \in N} \sum_{k \in V} x_{ij}^k = 1 \qquad \forall i \in N/P^p \tag{3.16}$$

$$\sum_{i \in N} \sum_{j \in N} x_{ij}^k \leq M * v_k \qquad \forall k \in V \tag{3.17}$$

$$\sum_{j \in N} x_{ij}^k - \sum_{j \in N} x_{i+n,j}^k = 0 \qquad \forall i \in P/P^t,\ k \in V \tag{3.18}$$

$$\sum_{j \in N} x_{oj}^k \leq v_k \qquad \forall k \in V \tag{3.19}$$

$$\sum_{j \in N} x_{ij}^k - \sum_{j \in N} x_{ji}^k = 0 \qquad \forall i \in P \cup D,\ k \in V \tag{3.20}$$

$$\sum_{i \in N} x_{i,2n+1}^k \leq v_k \qquad \forall k \in V \tag{3.21}$$

$$\sum_{j \in N} x_{0,j}^k = \sum_{i \in N} x_{i,2n+1}^k \qquad \forall k \in V \tag{3.22}$$

$$\sum_{j \in N} x_{i,j}^k - \sum_{j \in N} x_{N^t,j}^k = 0 \qquad \forall i \in P^t,\ k \in V \tag{3.23}$$

Constraints (3.15) and (3.16) ensure each customer node is visited exactly once by one pod, or the node could be skipped if it's a passenger pick-up node, constraint (3.17) makes sure only if a pod is deployed could it travel in the network. Constraint (3.18) restrained every demand request that won't be transported to the train station will ultimately arrive at its destination, which is, the flow conservation constraint for each delivery order. Constraints (3.19) and (3.21) set up limitations on the departure node and destination node of each pod, which means pods can only depart from the depot and end their service trips at the depot, while (3.22) ensures the number of pods departing from the starting node is the same as the number of pods entering the destination node. Constraint (3.20) is the flow conservation constraint for each node in the network, it refers to each pod that should arrive at each non-depot node and then leave the node, to ensure the continuity of service trips.

Constraints (3.23) sets a specific routing constraint for train stations. It is assumed that the train station node can be visited by multiple pods.

Time-window constraints

The timeline of which the following constraints will set limits is demonstrated in the following sketch:

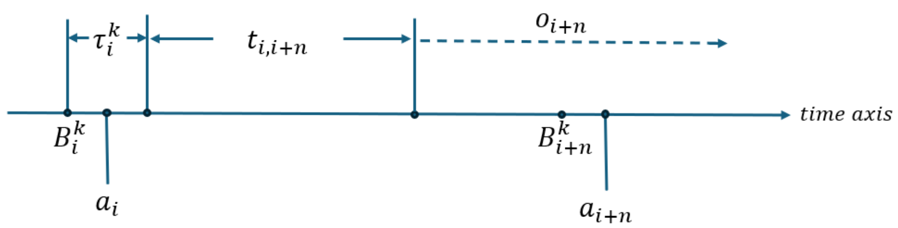

Figure 3.3: Timeline

As is denoted in the figure, for each node i, there is an expected arrival time a_i. The reason for introducing this variable is that when calculating the penalty for early and late arrival in the objective function, it is necessary to keep these two values non-negative, thus it requires two more variables. In order to minimize the number of decision variables, an assumption is made that no pods should arrive at a node earlier than the expected arrival time. For the late arrival time l_i, it is a non-negative variable.

$$B_j^k \geq \left(B_i^k + \tau_i^k + t_{ij}\right) - M(1 - x_{ij}^k) \qquad \forall i, j \in N,\ k \in V \tag{3.24}$$

$$B_{i+n}^k \geq (B_i^k + \tau_i^k + t_{i,i+n}) - M(1 - \sum_{j \in N} x_{ij}^k) \qquad \forall i, j \in N,\ k \in V \tag{3.25}$$

$$B_{i+n}^k - (B_i^k + \tau_i^k + t_{i,i+n}) - M(1 - \sum_{j \in N} x_{ij}^k) \leq o_i^k \qquad \forall i \in P/P^t,\ K \in V \tag{3.26}$$

$$B_{T_d}^k - (B_i^k + \tau_i^k + t_{i,T_d}) - M(1 - \sum_{j \in N} x_{ij}^k) \leq o_i^k \qquad \forall i \in P^t,\ K \in V \tag{3.27}$$

$$B_{2n+1}^k - B_0^k \leq T_k \qquad \forall k \in V \tag{3.28}$$

$$B_i^k \geq a_i \qquad \forall i \in P,\ k \in V \tag{3.29}$$

$$B_{t_p}^k + M(1 - \sum_{j \in N} x_{ij}^k) \geq a_i \qquad \forall i \in D^t,\ k \in V \tag{3.30}$$

$$B_i^k - a^i - M(1 - \sum_{j \in N} x_{ij}^k) \leq l_i \qquad \forall i \in P,\ k \in V \tag{3.31}$$

Time window plays a critical role in the planning process of each service, so do the relevant constraints on service network optimization.

Constraints (3.24) - (3.28) restricted the operation time windows from different perspective. Constraint (3.24) denotes that the arrival time of pod k at the following node j should be no earlier than the sum of arrival time and service time at node i and the travel time on arc (i, j) if pod k travels on arc (i, j), this constraint ensures temporal continuity between each two consecutive segments in a service trip. Constraint (3.25) ensures each delivery request's arrival time at its destination node should be no earlier than the sum of the arrival time of pod k at pick-up node i, service time at node i and travel time between pick-up node i and its corresponding drop-off node $i + n$. Constraint (3.26) allows the detour which takes place during the transport services, the consequence of introducing the detour will also be included in the objective function. Constraint (3.27) does the same thing as a constraint (3.26), the only difference between them is the pick-up node-set.

Constraint (3.28) bounds the upper limit for pod k finishing a single service trip, which is T_k. Constraints (3.29) and (3.30) forbids any pod k arrive earlier than expected arrival time at node i. Lastly, constraint 3.31 calculates the delay of pod k when arriving at node i, this term l_i will be returned to the objective function to calculate the tardiness penalty.

Train station capacity constraints
As is stated in section 3.1, in the context of this project, a vital point to be considered is the capacity of the train station, as it can only be visited by a certain number of pods maximum in a specific time interval. For the sake of simplicity, we hereby assume the time intervals (denoted as ρ) are uniform, for example, 10 minutes. A diagram demonstrating the timeline of the train station approaching is as follows:

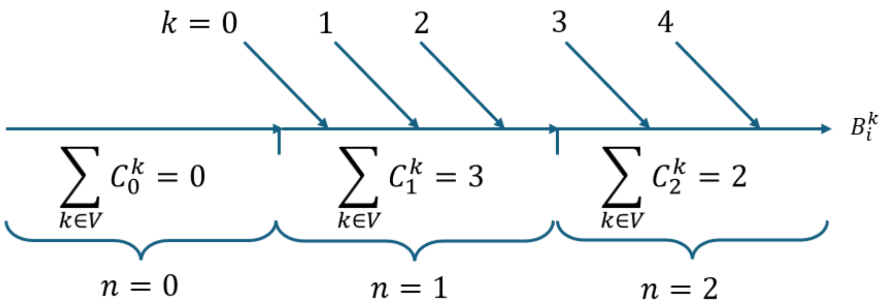

Figure 3.4: Timeline - Train station capacity

Thus, to restrict the inflow of the pods at the train station, the following series of constraints are proposed together with a fellow student (see [90]):

$$B_i^k = \rho Q_i^k + \rho \qquad \forall i \in T, k \in V \tag{3.32}$$

$$Q_i^k = \sum_{n \in I} n * C_n^k \qquad \forall i \in T,\ k \in V \tag{3.33}$$

$$Q_i^k - n \leq M(1 - C_n^k) \qquad \forall i \in T,\ n \in I, k \in V \tag{3.34}$$

$$Q_i^k - n \geq -M(1 - C_n^k) \qquad \forall i \in T,\ n \in I, k \in V \tag{3.35}$$

$$\sum_{k \in V} C_n^k \leq C^t \qquad \forall n \in I \tag{3.36}$$

In the constraints listed above, (3.32) introduces a new variable Q_i^k denotes the number of intervals the arrival time of pod k arrives at train station i. To give an example, if a pod arrives at the train station at 22^{nd} minute, then the pod arrives during the third time interval, thus Q_i^k equals to 2. (3.33)-(3.35) is a set of constraints help to set correct C_n^k to 1 when $Q_{T_p}^k$ is not zero, which means, the number n should be corresponding to the n in variable C_n^k. Lastly, (3.36) secures the initial target of this constraint set: limiting the inflow to the train station not exceeding train station capacity C^t.

3.3.5. Connecting packing constraints with routing constraints

In this section, we'll strive to integrate the two sub-models proposed in the previous sections 3.3.4 and 3.3.3 to form a comprehensive model.

Several methods were attempted to connect both the pickup-and-delivery process and the bin-packing process. However, mathematically connecting them is quite challenging to implement, as packing during the pickup and delivery process is dynamic. We need to introduce several other time-related variables to accomplish the goal of removing cargo from the pods when they reach their destinations, particularly concerning the space and pivot coordinates. This will inevitably increase computational complexity, as the entire model will be categorized as dynamic programming. Transforming the problem into a dynamic programming challenge is not only time-consuming but also beyond the scope of this thesis project.

An alternative option is to design a dedicated metaheuristic algorithm to assist in solving this complicated combined model since it is unnecessary to consider the dynamic process during the pickup and delivery stages. The initial solution construction and searching process in the most commonly used neighborhood searching algorithm inherently integrates the dynamic process itself. The bin-packing component will solely serve as a feasibility-checking tool. However, this approach is not advisable due to its high programming complexity and the presence of research groups already engaged in it.

Therefore, a simpler method is applied to integrate these two models. The core idea about how to merge the two models is to solve them sequentially. The process of solving the whole question is decomposing it into two sub-questions, then solving them one by one.

In the first stage, we solve the PDVRP and provide the best routing plan for a problem instance under the current parameter setup. Then, in the second phase, we check the feasibility of the current packing scheme with the 3D bin-packing model proposed in Section 3.3.3. If the packing scheme is proven to be feasible, we retain the current routing scheme and record the value of the objective function as well as all the penalty components for sensitivity analysis carried out in Chapter 4.

In case when the packing scheme is infeasible, we will adhere to the results provided by the bin-packing model regarding how many additional pods will be necessary to meet all the demands specified in the routing plan, and calculate the cost of deploying extra vehicles, this extra cost will be added to the objective function.

A flow diagram regarding how the model solving process is implemented in this thesis is shown in Figure 3.5.

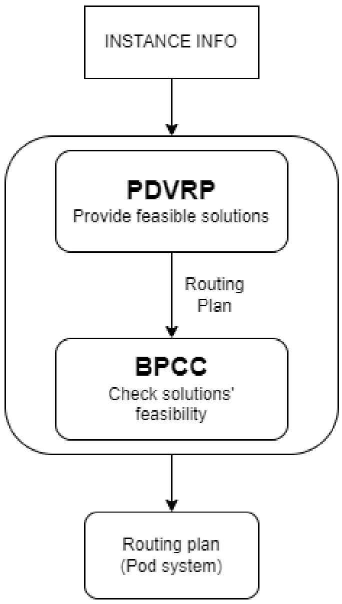

Figure 3.5: Routing and packing model integration

3.3.6. Integral and non-negativity constraints

The following constraints (3.37) - (3.49) will define the value of variables used in this chapter.

$$x_{ij}^k \in \{0,1\} \qquad \forall i, j \in N,\ k \in V \tag{3.37}$$

$$y_{ik} \in \{0,1\} \qquad \forall i \in N,\ k \in V \tag{3.38}$$

$$v_k \in \{0,1\} \qquad \forall i \in N,\ k \in V \tag{3.39}$$

$$s_i^p \in \{0,1\} \qquad \forall i \in P^p \tag{3.40}$$

$$f_{rk}^v \in \{0,1\} \qquad \forall r \in \Gamma,\ v \in J,\ k \in V \tag{3.41}$$

$$C_{rs} \in \{0,1\} \qquad \forall r, s \in \Gamma \tag{3.42}$$

$$c_{ij} \geq 0 \qquad \forall i, j \in N \tag{3.43}$$

$$t_{ij} \geq 0 \qquad \forall i, j \in N \tag{3.44}$$

$$B_i^k \geq 0 \qquad \forall i \in N,\ k \in V \tag{3.45}$$

$$e_i \geq 0 \qquad \forall i \in N \tag{3.46}$$

$$l_i \geq 0 \qquad \forall i \in N \tag{3.47}$$

$$B_i^k \geq 0 \qquad \forall i \in N \tag{3.48}$$

$$C_n^k = \{0,1\} \qquad \forall i \in N \tag{3.49}$$

4
Case study

4.1. Background introduction

The problem instance used for sensitivity analysis is mainly based on the dataset collected from Stockholm, Sweden. This dataset was also applied in two recent research[18][91]. The full dataset consists of 54 different data sheets; each sheet is contained in one Excel file. These sheets differ one from another in terms of varying node distributions, time window settings, and different periods in a day. Each sheet contains around 100 nodes, with coordinates, ready time, due time, service time, and service type given.

Considering that this dataset only provides the necessary data for PDVRP, we need to generate the other part of the data, which describes the characteristics of items to be picked up and delivered in this network. Therefore, the random number generator in Excel is applied to generate each freight item's width, length, height, and weight. The passengers are given a fixed dimension of 1.2*1.2*1.8(m) and a weight of 75kg.

Furthermore, each item is assigned a category since we also discussed the compatibility issue in the previous chapters. The dataset was randomly divided into four categories, and a compatibility matrix was also randomly generated, as shown in the following Table 4.1.

Table 4.1: Cargo compatibility matrix

Category	1	2	3	4
1	0	0	1	1
2	0	0	0	0
3	1	0	0	0
4	1	0	0	0

During the test run, we found out that applying any of the single data sheets will lead to a consequence that no results can be provided by the Gurobi solver in a reasonable time. Thus, for the test run of sensitivity analysis, we keep the data sheet to a minimum scale, which is enough to contain every different kind of node while not increasing the computational complexity. The test dataset applied in the following sections consists of 12 nodes, namely 2 depot nodes, 2 train station nodes, 3 different pickup nodes and 3 different delivery nodes. The nodes included in the problem instance to be analyzed are chosen from the given dataset. In this problem instance, the train station nodes are defined by geographical locations, which is exactly the spot of a train station located in Stockholm, the other nodes are characterized randomly.

The distribution of the nodes in the designed problem instance on the map is shown in Figure 4.1, the background map is loaded from OpenStreetMap.

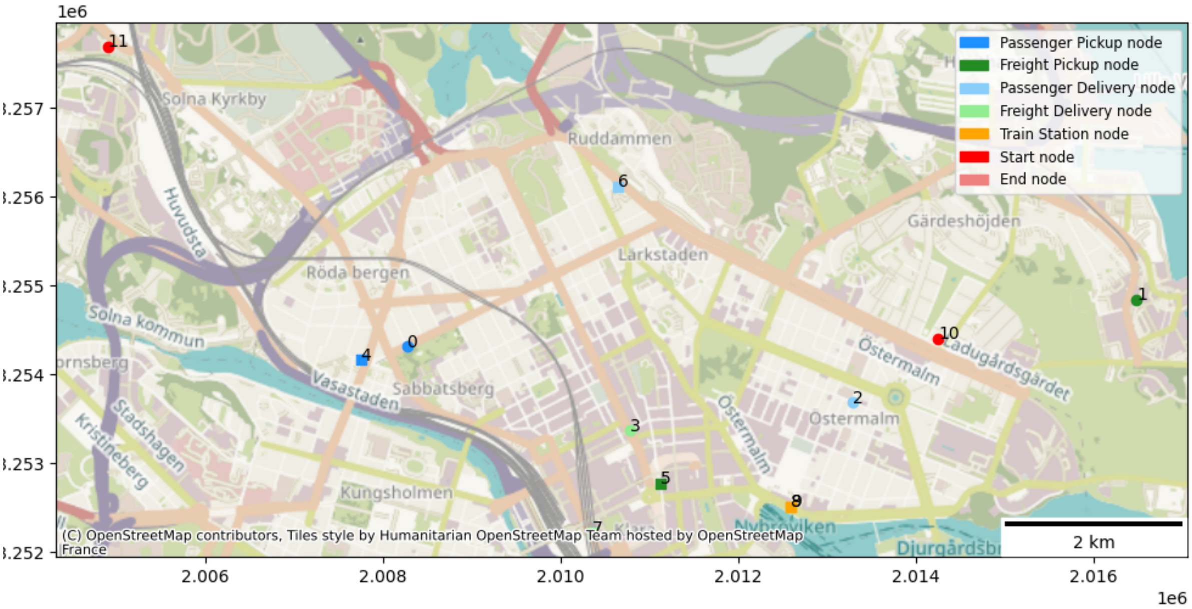

Figure 4.1: Network geographical setup

Similar to the items that will be packed in the pods, the pods themselves are given a standardized geometrical dimension for the interior space as well as a fixed weight capacity. They will be listed in Table 4.2 in the next section.

Furthermore, to measure the optimality of this POD system, we would like to introduce a traditional transport system serving freight and passenger demands separately as a benchmark. This traditional transport system consists of two parts: a "Private car" system responsible for passenger demand transportation and a "Vans" system responsible for freight demand transportation. The basic model for solving the routing problem for these two systems will be almost the same as what we proposed above. The traditional transport systems run on the same road network and traverse all demand nodes respectively.

To further differentiate the traditional transport systems from the PODs system in the mathematical model, several features are adapted. For the two traditional transport systems, the detour problems and demand skipping option will not be considered, as they are dedicated transport systems, also, the cargo compatibility problem will not be taken into consideration as well. For every parameter setup examined in the sensitivity analysis carried out in Chapter 4, we will compare the objective function value of both PODs system with the two traditional systems, as well as their combination. A flow chart demonstrating this comparison and evaluation process is shown in the following Figure 4.2.

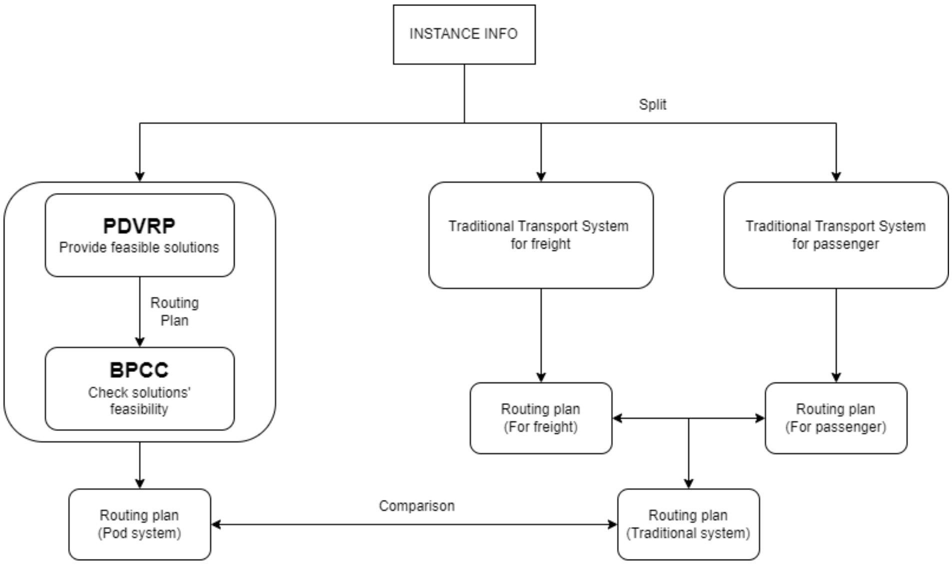

Figure 4.2: Comparison model across different systems

4.2. Parameter setting

The parameter values used as the baseline of the sensitivity analysis carried out in this chapter are determined in different ways, some are obtained from existing literature, while others are more logical based. This suggests that the results obtained in this chapter are merely for reference, but this shouldn't have an influence on the validity of the conclusions. The parameters applied in the sensitivity analysis are listed in the following Table 4.2.

The value for the maximum throughput at the train station is set to 5 pods per 5 minutes. The train station throughput becomes important if the model is used with a significantly larger dataset. In this sensitivity analysis, however, the maximum number of pods is exactly 5. Thus, the maximum throughput capacity of the train station will not exceed the limit. Another consideration of setting a maximum capacity in this manner is that calculating throughput for a longer discrete time interval can not only simplify modeling difficulty but also reduce computational complexity.

The introduction of travel time between nodes is because we can only calculate Euclidean distance between the nodes based on the dataset. However, this is not realistic, as the local road network is not a grid road network. Thus, we introduce the travel time between nodes to compensate for the difference between Euclidean distance and the actual driving distance between two nodes. Travel time prediction is used as per the data provided by Google Maps between 10 randomly chosen OD pairs. Using this, the average driving speed (v_{pod}) is calculated using the Euclidean distance. The average speed of the pods during a normal service trip is approximated as 10 km/h. With these two assumptions, the full travel time matrix is calculated using the following equation:

$$t_{i,j} = \frac{60c_{i,j}}{v_{pod}} \tag{4.1}$$

with $c_{i,j}$ being the Euclidean distance calculated directly from geographical coordinates with the haversine equation. The value of 60 ensures that the travel time ($t_{i,j}$) is calculated in minutes.

Table 4.2: Parameter values used in the sensitivity analysis

Symbol	Description	Value	Unit
Train station characteristics			
C^t	Max. throughput of the train station per period	5	Pods
ρ	Minutes of one time interval	5	minutes
Pods characteristics			
W	Width of pods' interior space	2.4	meters
H	Height of pods' interior space	2.5	meters
D	Depth (Length) of pods' interior space	6	meters
$Weight$	Maximum weight of freights a pod can load	850	kg
v_{pod}	Average travel speed of pods	10	km/h
Penalty costs			
α_p	Demand skipping penalty	20	per node
α_k	Penalty for using a pod	20	per pod
α_c	Travel distance penalty	2.5	per km
α_l^f	Tardiness penalty for freight	2	per min
α_l^p	Tardiness penalty for passenger	2	per min
α_o^f	Detour penalty for freight	0.15	per min
α_o^p	Detour penalty for passenger	0.1	per min
Other			
n_P	Number of pickup nodes in set P^-	4	nodes
n_N	Number of pickup and delivery nodes combined	10	nodes
n_E	Total number of intervals	10	intervals
M	Big-M value	1500	-

4.3. Model computation

This section will provide the computing result in a larger problem instance, which is currently determined as a 22-node network. A trial run of 24 hours will be carried out, and we will analyze how the objective value and optimality gap change over time.

The results used in the following sensitivity analysis section are all computed by Gurobi solver 11.0.2 on a laptop computer equipped with AMD RYZEN 9 8945H @ 4GHz (8C16T) with 32GB RAM memory. To keep the computation time short, the dataset used in the next section is small, with only 12 nodes in total and could be solved by the laptop within a minute. In order to test the complexity of this PDVRP model, we chose to run it with a larger dataset with 22 nodes, which was tested in the early phase of model development and was deemed too complicated for any laptop to solve in a reasonable time period. To better carry out this test, we deployed a desktop equipped with Intel Core i7-14700K @ 5GHz (20C28T) with 64GB RAM memory and ran it for 24 hours.

As is shown in the Figure 4.3, the optimality gap after 24 hours' running was still as high as 74.7%. Clearly, the high optimality gap makes the result of the objective function value we get from the model unacceptable. This is the main reason to use a much scaled-down model in the following sensitivity analysis sections.

The smaller dataset applied in the upcoming sections only contains 12 nodes, and can be solved by Gurobi on the laptop within a reasonable amount of time. The computational performance indicators are demonstrated in the following Figure 4.4:

4.4. Sensitivity analysis

This section is the main focus of this chapter. In this section, we perform a sensitivity analysis of the studied Problem of PDVRP with 3DBPCC, especially for the mathematical model formulated in Chapter 3. The sensitivity analysis aims to evaluate the influence of parameter variations on the performance and outcomes of the model, offering insights into its robustness and practical applicability. Specifically, we focus on the parameters associated with the objective function, which encapsulates

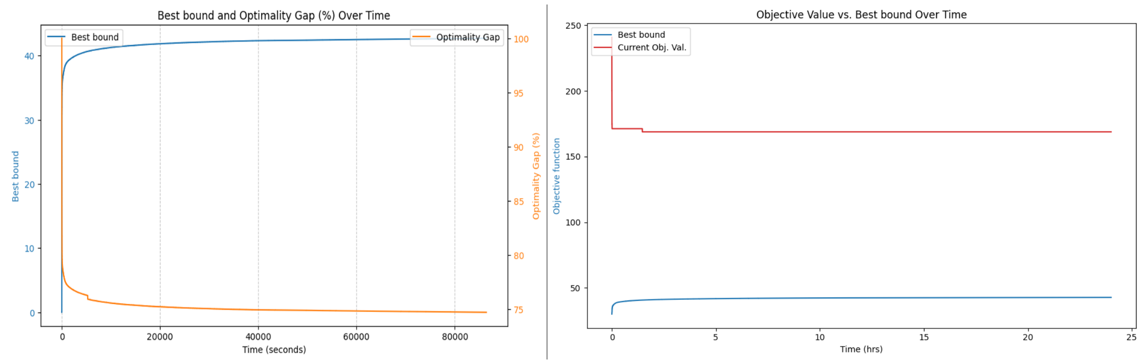

Figure 4.3: Objective value, Optimality gap and Best bound over 24 hours - big dataset

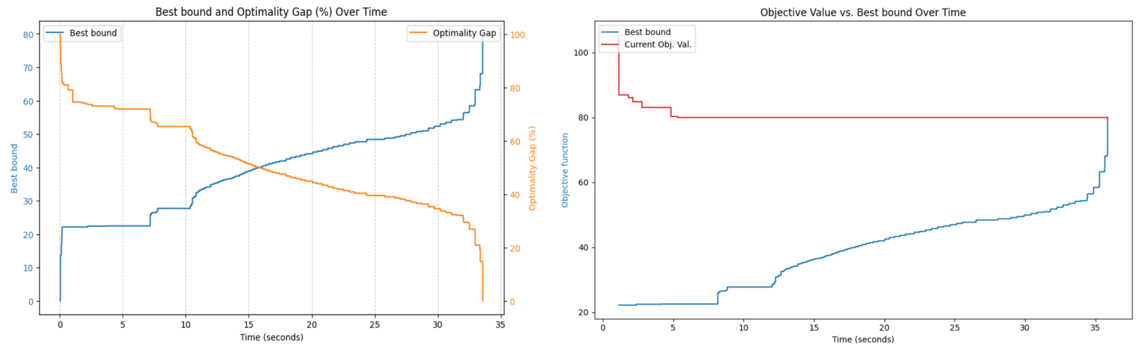

Figure 4.4: Optimality gap, Objective value and best bound for sensitivity analysis - standard setup

multiple conflicting optimization goals. These parameters are systematically adjusted to assess their impact on critical performance metrics.

The analysis delves into several key aspects, including the routing plan obtained by the model, how the weight coefficient of different cost components, namely the travel distance penalty, the demand skipping penalty, the detour penalty, and the tardiness penalty, will exert their impact on the routing decision. Furthermore, we will explore how two of the realistic factors, the travel speed of pods and the train stations' capacity, influence routing decisions and some critical performance indicators as well. By exploring these dimensions, the sensitivity analysis highlights the trade-offs inherent in the optimization process, while also serving to deepen the understanding of the research question and reinforce the utility of the proposed model in addressing real-world challenges.

In addition, to measure the effectiveness of the POD system, we compare the objective function value, as well as each component mentioned in 3.1, with exactly the same parameter settings, in two "traditional transport systems". These two systems provide transport services to passengers and freight respectively, and both systems follows the routing model proposed in Chapter 3. As for the bin-packing problem, we wouldn't draw attention to the packing scheme's feasibility for the passenger segment since passenger demand is too few to fill up the capacity of one pod under the current network setting. For freight demands, we will consider both routing and bin-packing models. After solving the model under the scenario of these two transport systems, we add the objective function value up to obtain the total cost of the traditional transport system. In the sensitivity analysis, we will not only compare the total costs of these two different approaches, but also provide insight into some performance metrics beyond just cost values, such as the average distance traveled by each pod and the proportion of deadheading distance during service trips.

4.4.1. Benchmarking

To assess the cost-efficiency and operational performance of the proposed POD-based transport system, we conduct a benchmarking analysis against two conventional transport systems proposed in section 4.1. By evaluating key performance indicators—including total travel distance, deadheading proportion, tardiness penalties, and overall system cost—under consistent parameter settings and demand conditions, this comparison aims to highlight the relative advantages and limitations of each approach. The parameter settings for the PODs system are listed in the table 4.2. For comparison, the parameter settings for the two traditional transport systems are defined as closely as possible to those of the PODs system. In practice, the detour penalty coefficients are set to 0 (since detour penalties are not considered in the two traditional transport systems), and we provide as many vehicles as possible for transporting the demands for the two traditional transport systems, the other parameters are kept exactly the same as what we used for the PODs system.

The results, as listed in the following Table 4.3, provide a quantitative basis for evaluating whether the integrated, autonomous POD system offers a more efficient alternative to traditional transport configurations.

Table 4.3: Benchmarking results

	PODs	Private cars	Vans	Traditional transport system
Travel distance penalty	48.425	30.225	39.4	69.625
Pod usage cost	40	20	40	60
Demand skipping penalty	20	0	0	0
Detour penalty (freight)	4.404	0	0	0
Detour penalty (passenger)	0	0	0	0
Tardiness penalty (freight)	5.12	0	1.32	1.32
Tardiness penalty (passenger)	2.34	25.54	0	25.54
Total cost	120.289	75.765	80.72	156.485
Total travel distance	19.37	12.09	15.76	27.85
Extra vehicle used	1	0	0	0
Extra vehicle usage cost	20	0	0	0
Driver cost	0	3.75	5.75	9.5
Total cost	140.289	79.515	86.47	165.985

As could be seen in the table above, compared to the total operational cost of the two traditional systems, the PODs system holds an advantage in terms of travel distance penalty, pod usage penalty, and passenger tardiness penalty. Although introducing the detour penalty for the PODs system slightly increased the overall operational cost, this term is still small enough not to conceal the advantage of the PODs system.

Regarding Travel Distance Penalty, under the default parameter settings, the penalty value associated with the POD-based system is significantly lower than that of the two conventional transportation systems, with a reduction of approximately 30%. When the travel distance penalty is converted back to actual travel distance, the saving becomes even more evident—the total travel distance in the POD-based system is approximately 8.5 km shorter than that of the conventional systems. A further breakdown of this difference reveals two primary sources of distance savings in the POD-based system.

First, fewer vehicles are used, leading to a reduction in overall vehicle mileage. Simulation results show that the deadheading distance for the POD-based system is 2.44 km, accounting for 12.6% of its total travel distance. In contrast, the combined deadheading distance for the conventional systems is 4.09 km, representing 14.69% of their total travel distance.

Second, the POD-based system has an inherent advantage in selectively skipping certain passenger transport demands. In cases where a specific origin-destination (OD) pair is relatively far apart, private cars in the conventional systems are required to fulfill this demand, resulting in considerable additional travel distance. The inefficiency associated with this OD pair contributes not only to the travel distance penalty but also to time-related penalties, particularly tardiness penalties.

Since the detour issue in conventional transport systems was deliberately excluded during the control group design (as discussed in Section 4.1), this section does not compare the detour penalties across the different systems.

Regarding tardiness, the POD-based system generally performs worse due to its dual responsibility for both passenger and freight demands. Simulation results show that there is delay at some nodes in the POD system, with an average passenger demand delay of 2.34 minutes per node. This is still better than the average delay of 13.38 minutes per node observed in the passenger-only system (notably at nodes 0 and 4), the reason why this phenomenon happens is that the geographical positions of these two nodes are far away from the others, which will inevitably lead to a longer travel time if the vehicles have to pay visit to these two nodes, and thus leading to a larger passenger tardiness penalty. In the PODs system case, since skipping passenger nodes is a possible option, the system would skip node 0 in exchange for saving travel distance and decreasing the passenger tardiness penalty (see discussion in section 4.4.6. However, for the freight demands, the POD-based system underperforms compared to the freight-only van-based system, because the PODs system doesn't skip all the passenger nodes within this road network. Accessing passenger node 0 would delay the visit time to the subsequent nodes on the route, which triggers a higher freight tardiness penalty.

Lastly, the driver cost is also calculated for the two traditional systems, the value of the driver cost is calculated according to the standard data from CBS, the monthly salary is transformed into hourly salary. The reason why the driver cost for the PODs system is zero is because of its autonomous nature.

Based on the comparison above, summing up the total costs of each system reveals that, even when accounting for the use of an additional pod due to incompatible cargo, the newly designed POD-based system still incurs a lower total cost than the combined costs of the two conventional systems. This cost advantage is primarily attributed to a shorter total travel distance, a smaller fleet size, and the fact that the POD system operates autonomously, thereby eliminating driver labor costs. Overall, under the current parameter settings and geographical conditions used in this study, the POD-based system reduces operational costs by approximately 13.7%, demonstrating a significant cost advantage.

In the following section, we will conduct sensitivity analyses on various parameters and examine how changes in their values affect the system's overall routing and packing behavior.

4.4.2. Travel distance penalty (α_c)

In this subsection, we will explore how changes in the travel distance penalty coefficient would influence the overall objective value, different components of the objective function, and the system's behaviour.

The starting point of this coefficient is set at 2.5 penalty per km. This value is calculated based on a report published by a local consultant company, Panteia[92]. As per the description in the report, the general cost per kilometer in euros was 2.3 euros/km back in 2021. Considering general inflation, this figure is equivalent to 2.7 euros/km in 2024. So the starting point of this series testing is 2.5 euros/km. A total number of 9 different α_c values are chosen by scaling the original value from 0.1 to 10×, the simulation results are demonstrated as a bar chart in Figure 4.5.

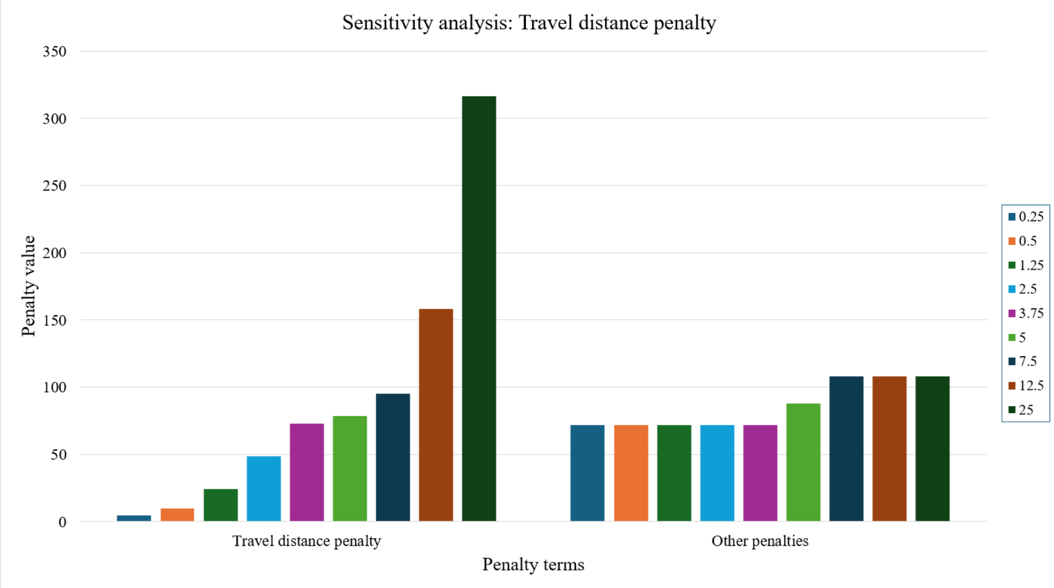

Figure 4.5: Objective value when α_c changes

As α_c varies, we observe that other components of the objective function do not undergo significant changes, especially when the scaling factor of α_c is small. When the scaling factor of α_c ranges from 0.1 to 1.5, the system's routing behavior remains unchanged. Within this range of α_c, the experimental results can be summarized as follows:

Firstly, the system deploys 2 pods to meet both passenger and freight demand, with a total travel distance of 19.37 km, including 2.44 km of deadheading distance. The deadheading distance mainly includes the distance traveled from the depot to the starting point and the return to the depot after completing transportation tasks. No deadheading occurs between nodes during transportation tasks.

Secondly, the passenger demand at node 0 is always skipped. From the map, node 0 is relatively far from other pickup nodes. Additionally, meeting the demand at node 0 (i.e., starting from node 0, delivering goods to node 2, and then visiting other nodes) requires extra travel distance and longer travel time, which may result in a higher tardiness penalty. This is likely the reason why the system skips this node.

Third, one of the pods, while performing transportation tasks, has to carry two incompatible demands from nodes 5 and 4 simultaneously. This necessitates deploying an additional pod. Considering the system design already accounts for autonomous driving and platooning, to simplify calculations, we only add the cost of using one additional pod, which is 20.

Lastly, although the fulfilled passenger demands still incur tardiness penalties at pickup nodes, there are no detour penalties. This indicates that the system has found the most direct possible route to node 4 for passenger pickup.

In subsequent adjustments to α_c, we found that the total travel distance of the pods, directly linked to this parameter, is not sensitive to changes in α_c. Changes only occur when the scaling factor reaches 2 or higher. When the scaling factor is 2 (i.e., $\alpha_c = 5$), the system further skips the passenger demand at node 4 while maintaining the configuration of using two pods to meet all freight demands. Beyond this, when the scaling factor reaches 3 or higher (i.e., $\alpha_c \geq 7.5$), the system further reduces the number of vehicles, using a single pod to meet all freight demands, even though this results in higher tardiness and detour penalties. A simple calculation shows that the benefit of reducing one pod and shortening the travel distance by 3 km (approximately 42.5) offsets the increased detour and tardiness penalties (40.562), making this change reasonable.

Regarding other data, it is worth noting that the pods' deadheading distance increases initially and then decreases as α_c rises. The proportion of deadheading distance to the total travel distance exhibits the same trend. However, while the absolute value of the deadheading distance is minimal in the sensitivity analysis when α_c is large, its proportion is relatively higher compared to the range of smaller α_c values due to the overall reduction in travel distance.

Since we introduced the comparison between the PODs system and the two traditional transportation system, we would also like to compare how the changes in travel distance penalty coefficient would impact the routing results of both systems. The results of travel distance penalty and the actual travel distance of both the PODs system and the two traditional systems (marked as "traditional" in the legend) combined are demonstrated in the following Figure 4.6.

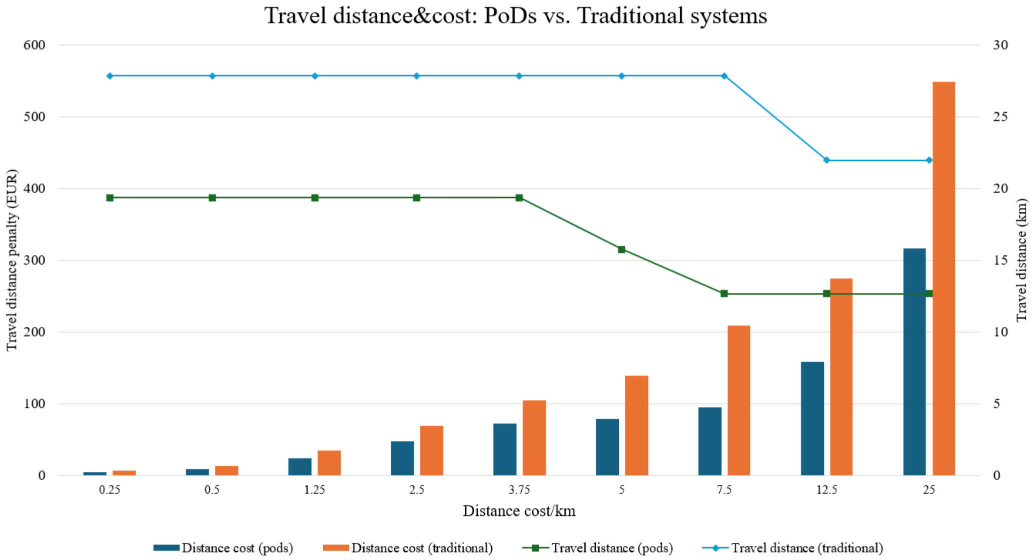

Figure 4.6: Comparison: traditional transport system vs. PODs system

From the figure above, we could observe that for the "traditional transportation systems" of cars and vans, their primary disadvantage compared to pods is the additional vehicles required for separate passenger and freight transport and the associated extra travel distance. When α_c is small, as passenger demands are not entirely skipped, the data shows that the total travel distance of traditional passenger and freight systems is approximately 43% higher than that of the PODs system. When α_c is large, the total travel distance of traditional systems is at least 70% higher than that of the PODs system, peaking when $\alpha_c = 7.5$. At this point, the PODs system has skipped all passenger demands, but passenger and freight demands are still completed by two vehicles each in the traditional systems.

Regarding delays, experimental data shows that under the current node distribution, the average delay duration of traditional systems is slightly advantageous across most tested α_c ranges. When α_c ranges from 0.1 to 2 times its initial value, the average delay of traditional systems is 0.6 minutes shorter than that of the new system. The advantage is most pronounced when α_c is three times the initial value. However, when α_c reaches five times its initial value or higher, the average delay of traditional systems increases significantly due to the reduced number of vehicles used. At this point, the average delay is about 1.5 minutes worse than that of the PODs system.

From the perspective of total costs, when the unit cost of travel distance is relatively low, the PODs system has an advantage over traditional systems in most cases, with exceptions (e.g., when $\alpha_c = 1.25$, the total cost of the PODs system is higher than the combined costs of the two traditional systems). However, when α_c exceeds 2.5, as the coefficient further increases, the cost advantage of the PODs system becomes increasingly significant.

Among the parameters that were not included in the test (or even in the model), we can still use a penalty to measure deadheading. If the goal includes the requirement of keeping the DH mileage ratio as low as possible, for example, if the transport provider attaches great importance to asset turnover efficiency, and the pure transportation cost per kilometer is relatively high (1.5x initial value or more), using traditional transportation methods can gain some advantages in this regard.

4.4.3. Demand skipping penalty (α_p)

Skipping passenger demand in a freight-centric transport system could bring several advantages. For example, it always reduces the distance traveled and has the added potential to reduce the tardiness penalty, detour penalty, or even the number of used pods.

In this section, a total of 9 different demand skipping penalty coefficients α_p are tested. Some clear trends are provided by the results demonstrated in Figure 4.7.

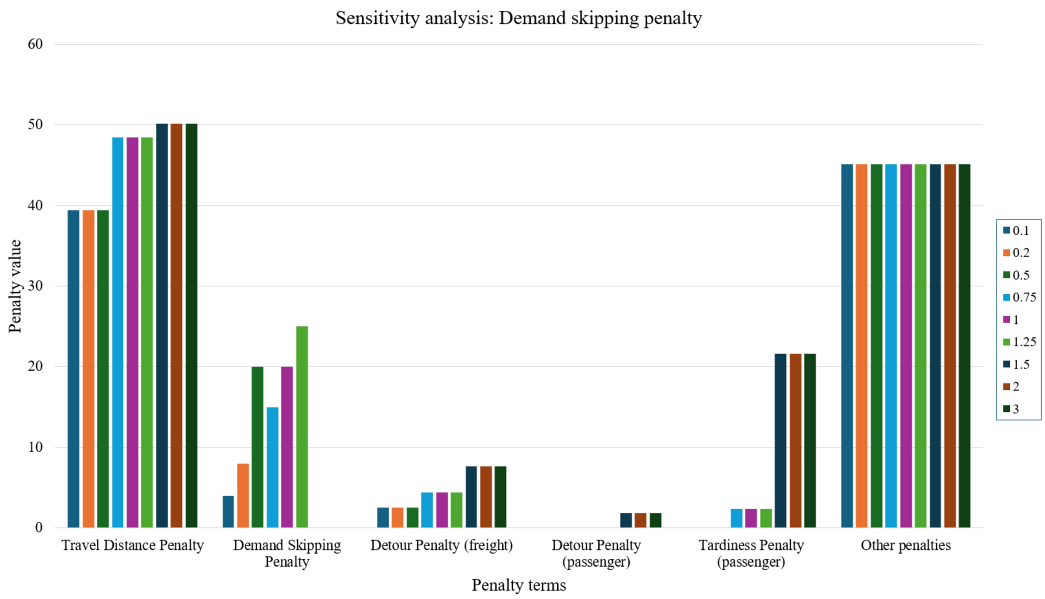

Figure 4.7: Penalty values when α_p changes

Under the initial parameter settings, the current optimized routing plan already skips one node. By adjusting the value of α_p, we can further observe that the changes in the system's routing results correspond to α_p values in three distinct phases:

1. $\alpha_p \leq 10$: the pod skips all skippable passenger nodes, achieving the minimum total travel distance and the lowest detour cost.
2. $\alpha_p \in [15, 25]$, the pod skips one pair of passenger nodes.
3. $\alpha_p > 25$, the pod does not skip any nodes.

The total travel distance of the pod increases sequentially across these three phases, and the freight detour penalty follows the same trend. However, the passenger tardiness penalty shows a significant increase in the final phase, indirectly explaining why passenger demand at node 0 is consistently skipped when α_p is relatively low.

Comparing the routing results of the PODs system and the traditional transportation system, we find that although the total cost of the PODs system is lower than that of the traditional system in the first two phases, the PODs system incurs a higher total cost in the third phase when α_p is large. This indicates that under the current system configuration, if there is a high demand for LoS (level of service) or if there are high-priority, non-skippable freight or passenger demands in the network, the cost of using the traditional transportation system would be slightly lower than that of the PODs system. We also need to notice that this situation is triggered by the incompatibility of freight boarding from node 5 and passenger boarding from node 4, which will lead to one more pod being deployed. In a more complicated network, this deficit can be much more obvious.

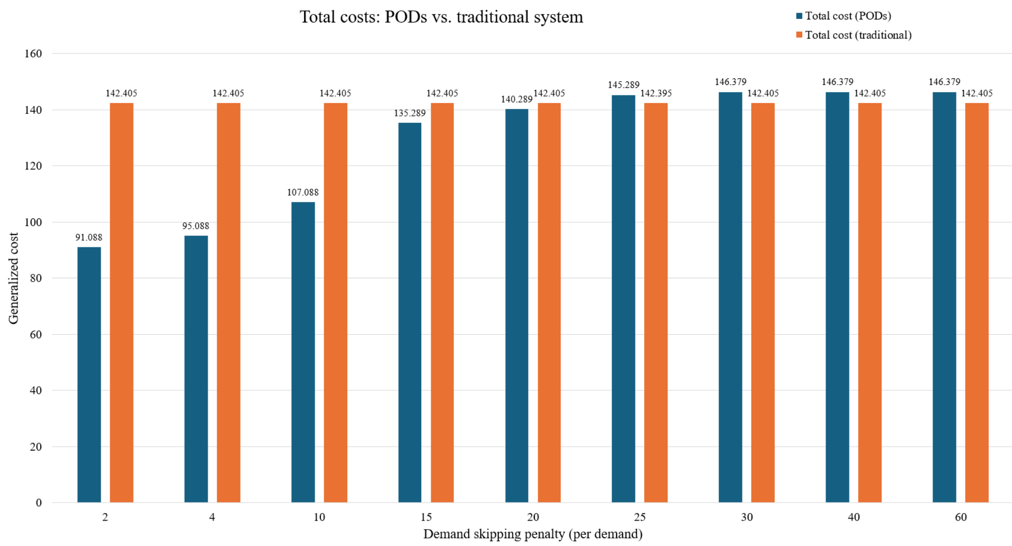

Figure 4.8: Total cost comparison: PODs and traditional system

4.4.4. Pod usage penalty (α_k)

The pod usage penalty indicates how many pods are deployed when serving transportation requests. The fewer pods a system uses to fulfill as many demands while maintaining its efficiency, the better for the infrastructure manager and other operation-related stakeholders. The following Figure 4.9 demonstrates how the value of α_k affects the behaviour of the system, and further influences different parts of the objective function.

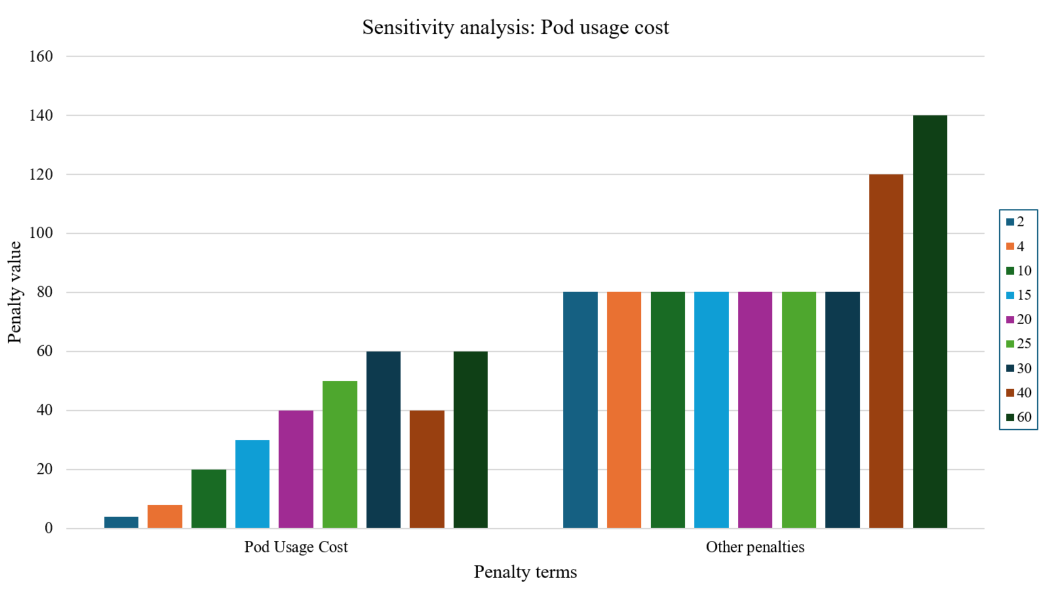

Figure 4.9: Penalty values when α_k changes

It is obvious that when α_k stands between 2 and 30, the routing result of the system is completely unaffected. When $\alpha_k \geq 40$, we can see a drop in the number of pods deployed for pickup and delivery tasks. This is because the decrease of pod usage cost offsets the increase of demand skipping penalty.

As the number of pods deployed decreases to 1, we can see some increase in the detour and tardiness penalty, the latter of which is significant. Node 1 contributes most of the increase in the freight tardiness penalty, which is in accordance with our judgment in the previous section.

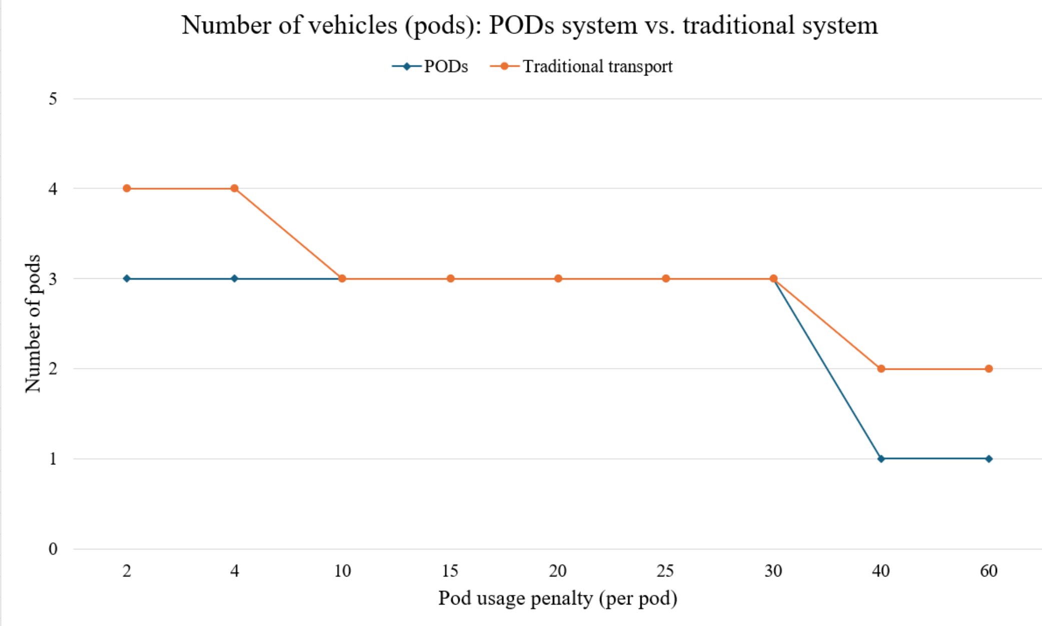

Figure 4.10: Number of pods used in two systems

For comparison, the same sensitivity test carried out in traditional transport systems indicates similar patterns. The only difference is that the private cars which serve the passenger demands, will only deploy 2 cars when α_k is very low ($0.1 - 0.2\times$ the initial value). With one car in service, the total travel distance decreased by 31.8%, but the passenger tardiness penalty grew significantly. Overall, the PODs system performs much better in terms of total travel distance (so as the deadheading distance). In terms of tardiness, we see that the PODs system holds an advantage under most of the α_k values, but when this parameter takes a large value ($\geq 2\times$ initial value), the traditional systems have smaller maximum and average tardiness values.

In conclusion, the objective function is not sensitive to the changes of the parameter α_k. The low sensitivity of this parameter is mainly caused by a relatively high travel distance penalty. If we set the α_c to $1/3$ of the initial value, we could see in this range that the system could deploy up to 4 pods to fulfill all the demands.

4.4.5. Detour penalty (α_o)

The detour penalty is applied for every additional minute a passenger or freight unit spends in a pod beyond the absolute minimum travel time. This can occur when the pod stops at extra nodes along the route from pickup to destination or when waiting before reaching the destination node is advantageous.

The detour penalty consists of two parts, one is the detour penalty for freight demands, indicated by α_o^f, the other is the detour penalty for passenger demands, indicated by α_o^p. Since the detour consists of one part of the travel time, the detour penalty coefficient is intentionally set to a small number to avoid double computation. The detour penalty generally contributes less than 5% of the total value of the objective function.

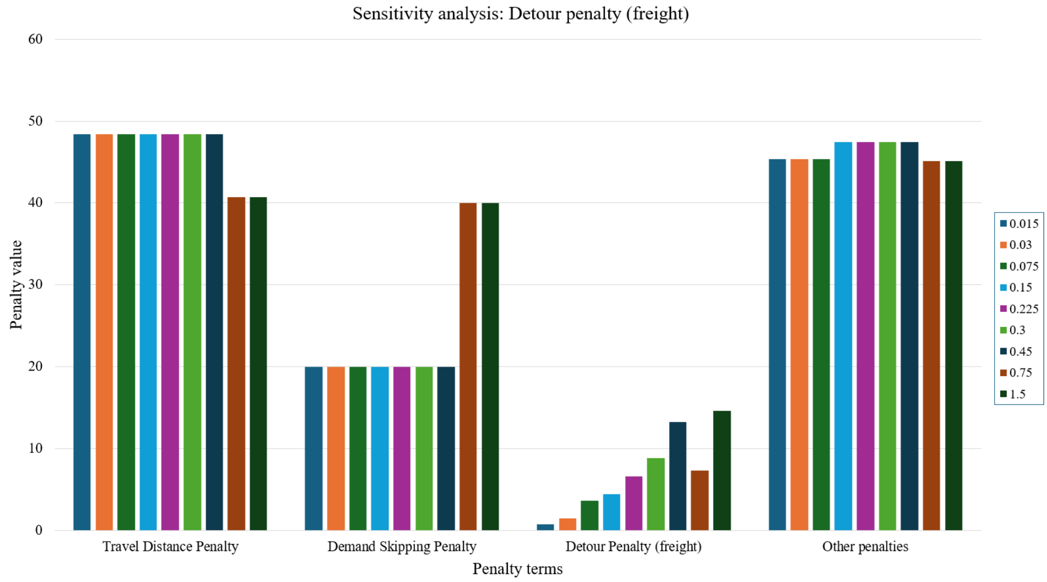

Figure 4.11: Penalty values when α_o^f changes

Under the current road network configuration, the system's routing behavior is highly insensitive to changes in the detour penalty coefficient, the reason of this could be that the detour penalties only contribute to so little portion of the total objective function, that we need to change the parameters α_o^p and α_o^f very drastically to see its impact on the result. Experiments reveal that only when α_o^f reaches 5 times its initial value or higher does the system's routing change, at which point the pods opt to skip an additional set of passenger demand nodes. This decision reduces travel distance and detour costs at the expense of unmet passenger demands.

Speaking of the peak values of detour penalty under different α_o^f, we can see from the following Figure 4.12 that there is a drop on the maximum freight demand detour when α_o^f increases from 0.45 to 0.75, this is caused by a shorter (and more direct) path taken by the pods, since it decides to skip all the passenger demands. Further experiments reveal that the detour penalty primarily competes with the tardiness penalty. When α_o^f is set to 20 times of its initial value, pods will prioritize the "theoretically shortest" route between pick-up and corresponding delivery node pairs, even if these routes result in significantly higher tardiness penalties.

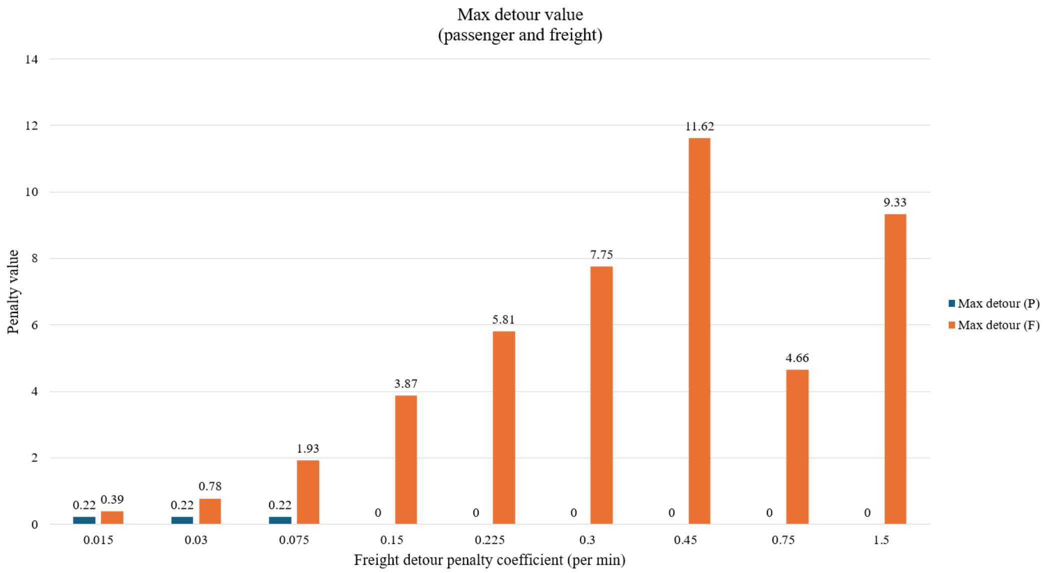

Figure 4.12: Maximum detour penalty in PODs system under each α_o^f

When it comes to the passenger detour penalty, a problem occurs under the initial parameter setting: the passenger detour penalty value remains 0 in most of the cases, this term only changes when the passenger tardiness penalty (α_l^p) changes. Thus, to observe the sensitivity of the coefficient of passenger detour penalty (α_o^p), some changes in initial parameter settings are made. The value of the parameters used for testing α_o^p are listed in the following Table 4.4

Table 4.4: Parameter values used for sensitivity analysis on α_o^p

Symbol	Description	Value	Unit
Penalty costs			
α_p	Demand skipping penalty	40	per node
α_k	Penalty for using a pod	10	per pod
α_c	Travel distance penalty	2.5	per km
α_l^f	Tardiness penalty for freight	2	per min
α_l^p	Tardiness penalty for passenger	1	per min
α_o^f	Detour penalty for freight	0.15	per min
α_o^p	Detour penalty for passenger	0.1	per min

The primary reason for using this set of parameter configurations is to minimize the influence of other parameters on the system's passenger pickup behavior, thereby allowing for more noticeable changes in the passenger detour penalty. To achieve this, we reduced the vehicle usage penalty and travel distance penalty while increasing the demand skipping penalty, ensuring that as many passenger demands as possible are fulfilled, and the changes in passenger detour penalty can be more obviously demonstrated.

Under the adjusted parameter settings, we still observe a similar issue to that encountered when adjusting α_o^f: altering the value of α_o^p generally has little impact on the routing results of the PODs system, as the model remains largely insensitive to variations in this parameter. The changing trends of the penalty terms with the change of α_o^p value is shown in the following Figure 4.13.

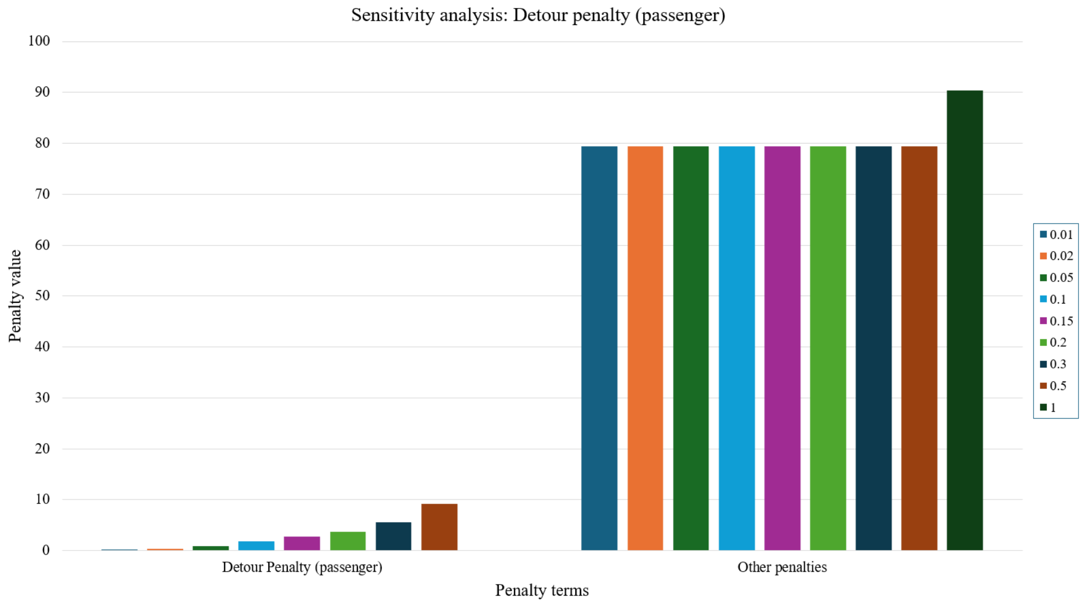

Figure 4.13: Penalty values when α_o^p changes

When α_o^p is within the range of 0.1-5 × initial value, the passenger detour penalty changes linearly, while the routing solution of the PODs system remains unchanged. However, when α_o^p exceeds five times its initial value, the system, now able to change the routing plan and deploy more pods. With α_o^p values approaching those of α_l^p and α_c, it naturally prioritizes reducing passenger detour and tardiness penalties while avoiding excessive increases in total pod travel distance. At this point, the system optimally deploys three pods, with the latter two pods each exclusively serving a single passenger demand. Although the total travel distance increases under this configuration, the passenger detour penalty is reduced to zero, and the tardiness penalty decreases by 37%.

Further validation reveals that additional changes in routing occur when α_o^p falls within the range of 0.5–0.6 × initial value. In most cases, a pod with a shorter planned route typically serves only one request, but within this range, it takes on two or three requests. This way the total travel distance of the pods increase, in exchange of the decrease in passenger tardiness penalty and detour penalty. We could come to a conclusion that the model is sensitive to the change of α_o^p within this specific interval.

Overall, significantly increasing α_o^p within the current parameter settings leads the system to accept longer total travel distances in exchange for lower time-related penalties, but we could still say that the system is not sensitive to the changes in the parameter α_o^p.

4.4.6. Tardiness penalty (α_l)

The tardiness penalty is calculated based on the difference between the actual arrival time of a pod at any node in the network and the expected arrival time for that node. In this section, tardiness is further divided into two components: the passenger tardiness and the freight tardiness. These two components are assigned different weights (α_l^p and α_l^f) in the objective function and are optimized accordingly. The tardiness penalty plays a critical role in balancing various sub-penalties during the optimization process. It is indirectly related to travel distance, detour penalties, and demand-skipping decisions, influencing the overall system behavior. The tardiness penalty plays a critical role in balancing the trade-off between meeting delivery or passenger demands on time and minimizing other cost components, such as travel distance or detour penalties.

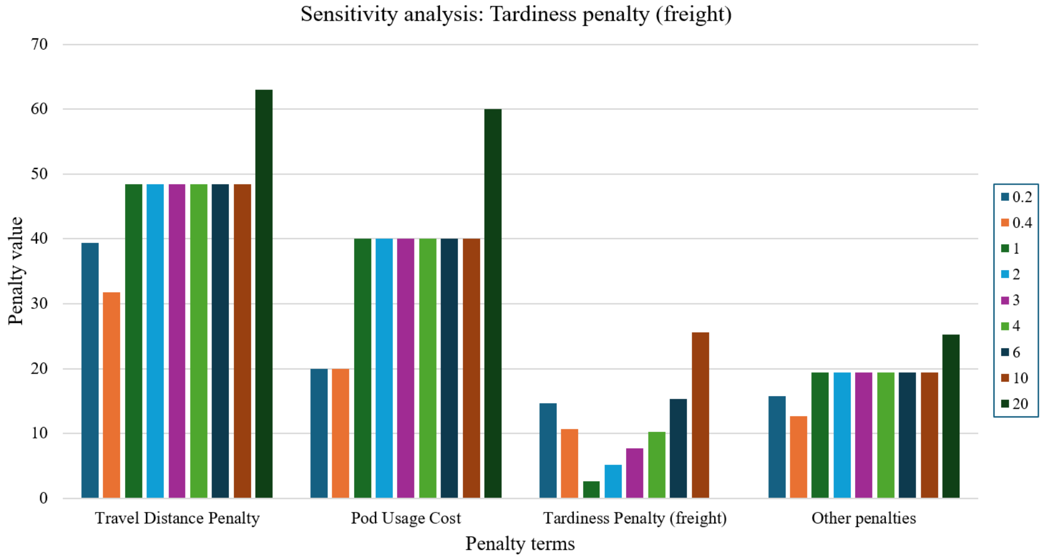

Figure 4.14: Penalty values when α_l^f changes

For the freight tardiness penalty, we began by setting $\alpha_l^f = 2$ and examined its effect on the system's overall routing behavior using nine different values. From the overall experimental results, the system demonstrates low sensitivity to changes in this coefficient across most of the tested range.

In the lower range of α_l^f (0.2–0.4), relatively higher delays are still acceptable to the system as a whole. During this stage, the tardiness penalty accounts for approximately 10%–16% of the total cost. The system utilizes only one vehicle to fulfill as many transportation demands as possible. At $\alpha_l^f = 0.4$, the system skips all passenger demand nodes to minimize the total cost, and the freight detour penalty remains at a low level (less than or equal to 1% of the total cost).

As α_l^f increases further, the system's optimal solution remains stable within the range of 1–10 for this coefficient. During this phase, only the freight demand tardiness penalty increases with the coefficient, while the delay time at nodes remains constant.

Finally, when α_l^f reaches 10 times its initial value or higher, the system deploys three vehicles to separately transport three different freight demands. In this configuration, the tardiness for all freight demands is reduced to zero. Beyond this point, further increases in the penalty coefficient are redundant, as the system has already achieved zero tardiness for all freight demands.

The average tardiness value and the maximum tardiness value of all freight demands, as well as those of all demands transported by the pods are shown in the following Figures 4.15 and 4.16.

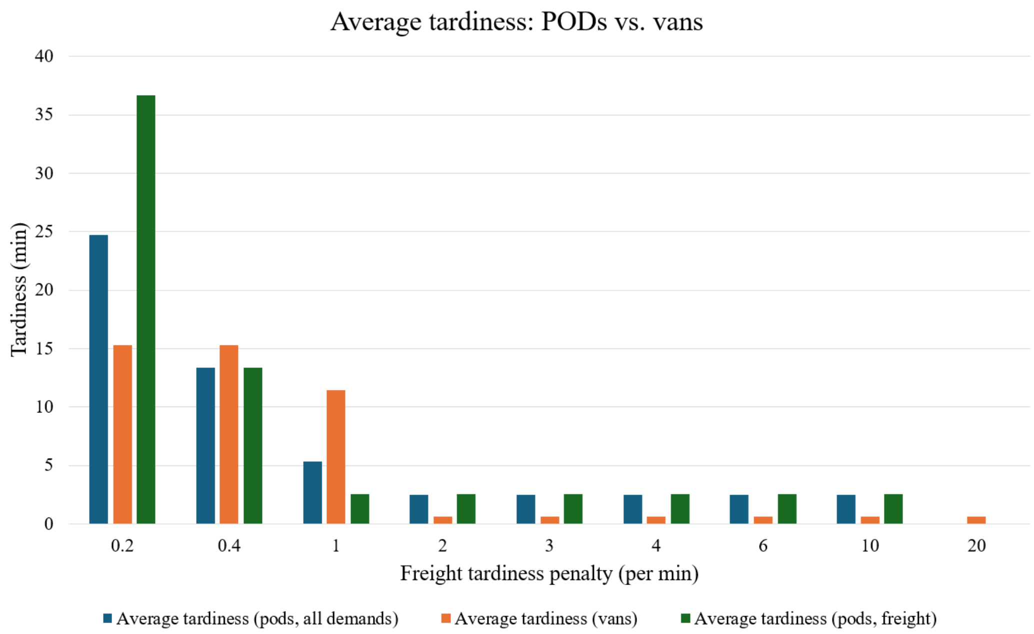

Figure 4.15: Average tardiness: pods vs. vans

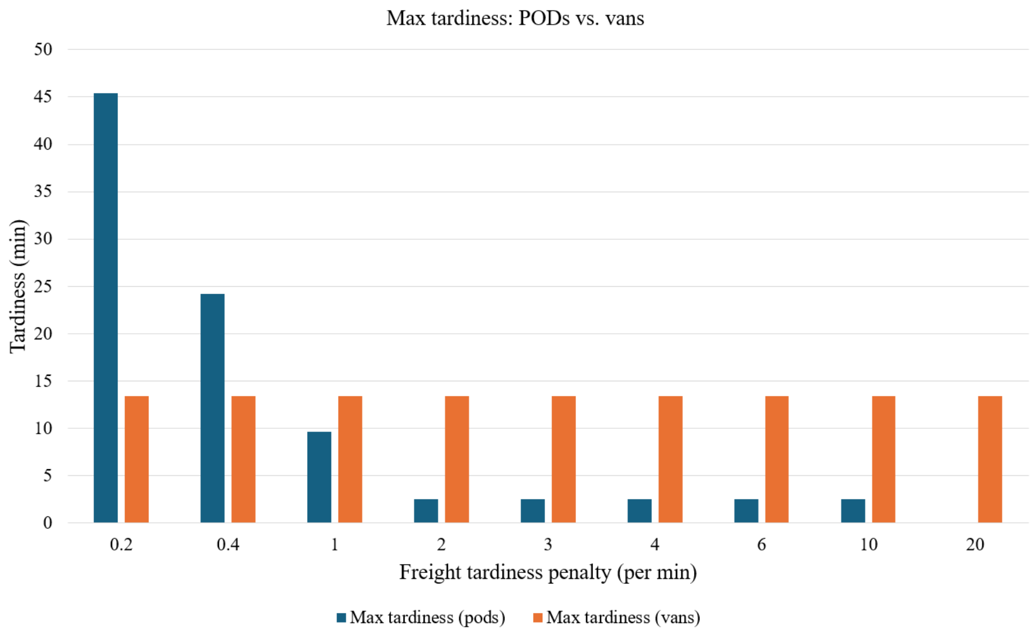

Figure 4.16: Maximum tardiness: pods vs. vans

Compared to the PODs system, the traditional transportation system (in this case, referring only to vans, as private cars are not involved in freight transportation) is unaffected by changes in α_l^f. Consequently, the tardiness at each node for fulfilling freight transportation demands remains constant. In the range of small α_l^f values (0.2–0.4), the traditional transportation system shows an advantage in terms of delay duration. Even when $\alpha_l^f > 1$, vans still exhibit a significant advantage in average tardiness compared to the PODs system. The total cost advantage of the vans system mainly stems from shorter travel distances and fewer tardiness minutes. However, when passenger transportation tasks handled by private cars are considered, the PODs system consistently outperforms the traditional transportation system.

For α_l^p, the sensitivity analysis reveals a similar trend to that observed for α_l^f, with the key difference being that the system is less sensitive to changes in α_l^p under the current configuration. Only when $\alpha_l^p \leq 1$ does the system avoid skipping any passenger nodes; beyond this point, it skips one passenger node. Additionally, when $\alpha_l^p > 1$, the system adjusts the node visitation sequence, leading to an increase in the freight detour penalty but a corresponding decrease in the passenger detour penalty. Most notably, when $\alpha_l^p > 1$, the system deploys an additional pod to minimize delays for passenger demands. From the perspective of the maximum and average delay times in the PODs system, both metrics decrease with increasing α_l^p before stabilizing.

Compared to the traditional private car mode, the PODs system shows a disadvantage in average delay times when α_l^p is within the range of 0.1–0.5. Beyond this range, however, the PODs system performs relatively better. A similar trend is observed for maximum delay times: at $\alpha_l^p = 0.1$–0.5, the private car system's maximum tardiness is 21.24% shorter than that of the PODs system. When considering only the tardiness of passenger demands, the disadvantage of the PODs system is even more pronounced in this range, as the PODs system prioritizes minimizing freight tardiness over passenger tardiness. Once $\alpha_l^p \geq 2$, the system's performance stabilizes.

Overall, regardless of the value of the passenger tardiness penalty coefficient, the PODs system consistently holds an advantage in total cost, with the advantage becoming more pronounced as α_l increases. Further exploration reveals that for a standalone private car system, the α_l^p value would need to be extremely high—at least 40 times the initial value—to influence routing decisions significantly. At such levels, which are nearly impossible in practical operations, this would equate to deploying two additional vehicles or incurring twice the penalty for skipping a passenger demand. Under these conditions, each passenger demand would be met by a dedicated vehicle. While this would drastically improve the system's level of service (LoS), it would have detrimental effects on environmental sustainability and energy consumption, which are not explicitly accounted for in the current model.

In summary, although changes in α_l^f and α_l^p have limited influence on the system's overall behavior due to the dominance of three larger parameters (α_c, α_p, and α_k), we still observed varying responses across different systems to changes in these coefficients. It is expected that experiments on larger datasets may reveal more pronounced effects. Additionally, since α_l^f and α_l^p work together to impact the system, future sensitivity analyses could explore adjusting the ratio between these two coefficients to better understand their combined influence.

4.4.7. Average travel speed (v_{pod})

The average travel speed (v_{pod}) directly impacts the travel time of pods between nodes, and its calculation method is detailed in the first section of this chapter. Changes to this parameter influence all time-related components of the objective function. During the variation of v_{pod}, all penalty components, except for the passenger detour penalty, showed significant changes.

When the average travel speed is set to be 10 km/h, the system begins servicing one additional passenger demand node. This leads to an increase in distance cost and a decrease in the demand skipping penalty. Although the freight detour cost increases slightly, and the passenger tardiness penalty is introduced at this speed, the freight tardiness penalty is significantly reduced.

Further increasing the pod's average travel speed to 1.5–2 times the initial value indicates that the system reduces the fleet size. to one pod while meeting as much demand as possible, once again skipping all passenger demands. When $v_{pod} = 2\times$ initial value, compared to 1.5×, both the detour penalty and tardiness penalty are further minimized.

When the average travel speed reaches 3 times the initial value (30 km/h), the system revisits one passenger demand node. This routing scheme is similar to the one when $v_{pod} = 10km/h$, but the pod's total travel distance is reduced by approximately 2 km. This reduction is attributed to the elimination of one pod's departure from the depot and its return after completing delivery. However, compared to the two-pod configuration, the passenger tardiness penalty more than doubles at this speed. Despite this increase, the penalty is relatively small, accounting for about 5% of the total objective function value, and does not become a high-priority component in the objective function, especially when the pod usage penalty has a significant weight.

Finally, when the average travel speed reaches 50 km/h, the system's routing results no longer skip any nodes. Although the freight tardiness penalty doubles compared to the scenario with a travel speed of 20 km/h, the freight detour penalty is halved. Further increasing the speed to 60 km/h, the routing scheme of the PODs system doesn't change anymore since no more demands await transport, the only changes in the objective function comes from a lower tardiness penalty. Considering the constraints of speed limits in urban areas and traffic conditions, higher average travel speeds are unrealistic and, therefore, not included in further experiments or discussions.

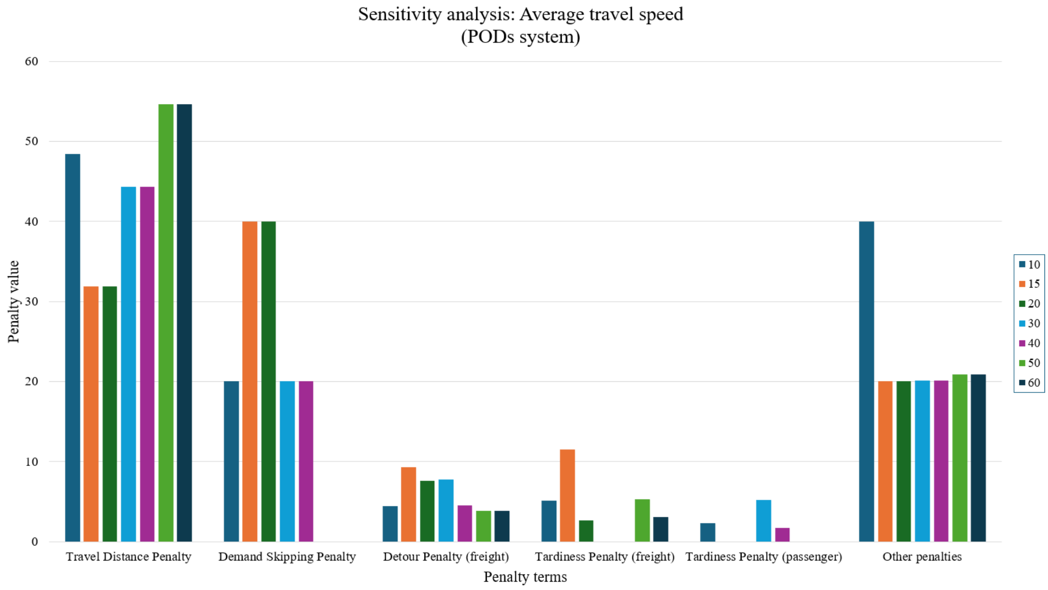

Figure 4.17: Objective function value under different average travel speed

For other penalty components, we observe that, with a consistent number of vehicles, the average delay time of pods across all visited nodes generally decreases. The only exception is when the average travel speed is 30 km/h, where both the average delay time and the maximum delay at a single node significantly increase compared to the surrounding values.

Additionally, an interesting phenomenon was observed during Gurobi's solving process: at $v_{pod} = 30km/h$, the solver's computation process was the slowest. After reviewing the solver's log file, it was found that, while the time to find an initial solution was consistent across different parameter settings, the number of nodes explored by Gurobi at this value was at least 50% higher than at other speeds. The reasons behind this behavior remain unclear.

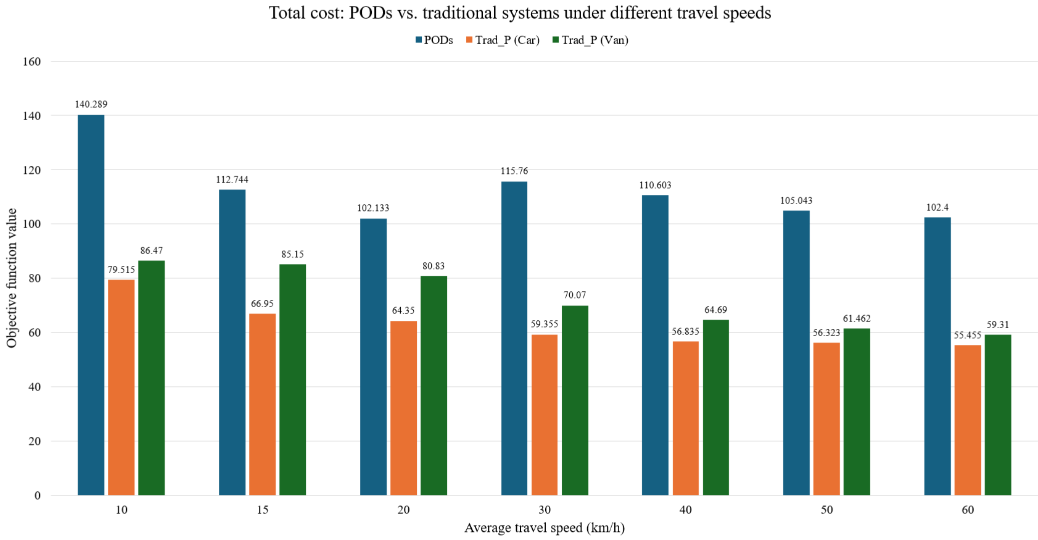

Figure 4.18: Comparison: PODs system vs. traditional systems

For traditional van and private car transportation systems, solving under these same seven average speed values reveals several recurring phenomena mentioned earlier:

For freight demands, the average tardiness of traditional systems is significantly lower than that of the PODs system when v_{pod} is in the range of 0.5-1.5 times the initial value. However, in the range of v_{pod} = 20-50 km/h, as the number of freight vans decreases to one, the tardiness advantage of traditional systems disappears.

Compared to the PODs system, the combined cost disadvantage of traditional passenger and freight systems, especially at lower average speeds, is primarily due to the need to separately transport passengers and freight. This results in additional vehicles and travel distances. The total travel distance of traditional systems can be up to 72.84% greater than that of the PODs system. However, as the number of vehicles and visited nodes stabilizes, the difference decreases with increasing average speed, eventually stabilizing at around 3%.

At higher average speeds, the difference in objective function values between the two systems is primarily due to the additional cost of using one more vehicle. This additional cost accounts for 69.7% of the total cost difference when the average speed is 50 km/h.

4.4.8. Number of pods

When analyzing the sensitivity of the system to the parameter of available pod numbers, we adjusted the initial parameter settings to ensure that changes in the number of available pods had a significant impact on the model's solutions. As mentioned earlier in the section on pod usage penalty, we found that the system only maximizes vehicle usage when both the travel distance penalty and pod usage penalty are set to very small values. To facilitate the sensitivity analysis in this section, we adjusted these two parameters and conducted experiments under the new initial parameter settings. The baseline parameter settings used in this section are shown in the Table 4.5 below:

Table 4.5: Parameter values used for sensitivity analysis on available number of pods

Symbol	Description	Value	Unit
Penalty costs			
α_p	Demand skipping penalty	20	per node
α_k	Penalty for using a pod	2	per pod
α_c	Travel distance penalty	0.5	per km
α_l^f	Tardiness penalty for freight	2	per min
α_l^p	Tardiness penalty for passenger	2	per min
α_o^f	Detour penalty for freight	0.15	per min
α_o^p	Detour penalty for passenger	0.1	per min

As shown in the table, the number of available pods in the initial settings was set to 5. In the current system network configuration, this number is sufficient to meet all transport demands. In fact, according to the optimization results from Gurobi, using 3 pods is already enough to ensure that the fleet completes all logistics tasks without skipping any transportation demands, but we also need to take compatibility issues into account, which would further increase the minimum required number of vehicle to 4. Using 5 pods represents the optimal solution under the current system configuration. In other words, the additional costs associated with using more vehicles, including extra travel distance and the cost of using an additional pod, cannot be offset by better performance in terms of time.

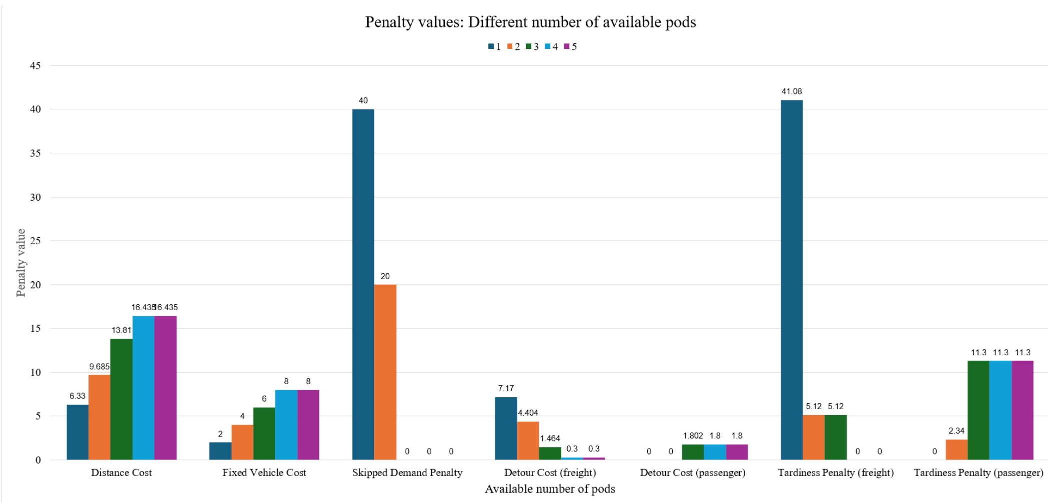

Figure 4.19: Penalty values' changes under different available number of pods

From Gurobi's optimization results, we can obtain the bar chart 4.19 above. In the figure, we can see that when the number of available pods is low, the demand skipping penalty constitutes the majority of the total cost. Specifically, when only 1 pod is available, the tardiness penalty for freight demands is also significantly high. Notably, node 1 accounts for 87.5% of the total tardiness in this scenario. The reasons for such significant tardiness at node 1 have already been analyzed in the section on travel distance penalty, so they will not be repeated here. This also explains why, when sufficient vehicles are available, the system prioritizes assigning a single pod to handle the 1-3 OD pair demand.

Additionally, while the system consistently incurs detour and tardiness penalties when meeting passenger demands, the penalties for freight demands continuously decrease as the number of available pods increases.

4.5. Discussion

This chapter conducted a sensitivity analysis on the weights of decision variables in the nine components of the objective function, as well as on other key parameters like the average travel speed of pods and the number of available pods.

Based on the data analysis above, it is evident that across most parameter ranges, the collaborative transport system demonstrates a cost advantage over the two representative traditional transport systems selected for comparison. Under the scenarios we established, the PODs system is shown to be worth promoting and has broad application prospects. The primary advantages of the PODs system over traditional systems lie in its use of fewer vehicles, which not only results in a lower pod usage penalty but also leads to shorter total travel distances and reduced deadheading distances. Additionally, from an environmental perspective—which is not explicitly considered in this study—the PODs system is likely to hold further advantages. However, it is important to note that the experimental conditions in this study do not fully represent the operational conditions of real-world systems. There is significant room for optimization, both in the parameter values themselves and in addressing factors not accounted for in the current model.

The findings highlight that parameters such as α_c and α_p have a significant impact on the system's routing decisions. For other parameters to have a more pronounced influence on routing, they generally require the combined effect of these two key parameters.

In MILP problems, interactions between parameters are inevitable. For instance, as shown in the section on the pod usage penalty, the influence of α_k alone on the model's routing outcomes is limited, particularly under the current settings of other parameters. However, when α_c is reduced to smaller values, subsequent adjustments to α_k show a much greater impact on routing results. Considering that the value of the total travel distance is significantly larger than other variables, such interactions are predictable. This also implies that in practical parameter tuning, special attention should be given to the pricing of road usage or transportation costs.

In future model optimization efforts, the distance penalty should be prioritized, followed by the pod usage penalty and tardiness penalty. The former typically has a higher unit cost, differs one from another when the vehicle changes, and significantly influences the model's outcomes, while the latter requires detailed discussions tailored to different passenger and freight categories, adding to the complexity of optimization.

For potential future research, more sophisticated methods could be applied to the sensitivity analysis, such as refining the analysis of interactions between different parameters or conducting a global sensitivity analysis. Additionally, with sufficient computational resources, larger datasets could be used to validate the results of sensitivity analyses under more complex scenarios.

5 Conclusion and envision

5.1. Conclusion

This research is motivated by multiple real-life problems, including low occupancy of road public transport services, proposals calling for greener transportation systems and the rise of modular transportation carrier design. Apart from this, we also see a lack of models in related studies that integrate the pick-up and delivery vehicle routing problem (PDVRP) with passenger-freight collaborated transport and intermodal features. These features are added to better align with real-world situations. Our research objective is defined as developing a mathematical model to solve the proposed operations research problem and selecting an appropriate algorithm to convert and solve the mathematical model, and finding a solution to the routing problem at the lowest possible cost within a short time.

The literature review provides insights into the development of models and algorithms related to two sub-models included in this thesis: PDVRP and 3D-BPP, together with their variants. Notable algorithmic approaches include Adaptive Large Neighborhood Search(ALNS), Variable Neighborhood Search (VNS), Tabu Search (TS), Stochastic and Genetic algorithms, Simulated Annealing, Greedy Randomized Adaptive Search Procedures (GRASP) for Vehicle Routing, Integer Linear Programming (ILP), and other specialized algorithms. Upon comparison, it has been found that the ALNS algorithm is a good choice for solving this problem. The research methods section delves into the steps of the ALNS algorithm and the criteria used in each step when solving different problems. These integrated studies provide a significant reference value for solving the current problem.

In the Problem Statement chapter, the background context on which this thesis is based on, the specific content of the mathematical model are presented. The model is based on, which is divided into three main parts based on different components of the whole research question. The first part established the model of a three-dimensional bin packing problem while considering the compatibility issue of different types of cargo, the second part contains the basic model constraints of the pickup and delivery problem, while it also addresses constraints limiting the number of pods accessing train station(s) in a specific period of time and the calculation on detour made by different pods.

The Case Study chapter provides a discussion on how the model and the heuristics algorithm behave in different testing instances. A sensitivity analysis is carried out not only to explore how the results of the system change under different parameter settings but also to show that the model is highly flexible to adapt to different scenarios with different user demands. This chapter also provides a comparison between the PODs system with two traditional freight and passenger transport systems, to prove that the PODs system is advantageous under most of the scenarios in the current parameter settings.

The main contribution of the research conducted is that we proposed a combined model based on PDVRP and a bin-packing problem, considering the compatibility issue of cargo. Furthermore, the PDVRP includes a pair of special nodes as the train station, which act as an interface between different transport modalities. The handling capacity and the time schedule are taken into consideration for routing decision-making. By adding these extra features to the original PDVRP and BPP models, this model moves one step closer to a realistic freight-passenger combined transport scenario, and provides some practical insight about the system's operational strategy.

The research question, *"How can we design a mathematical optimization model to optimize the operational performance of a passenger-freight integrated, 3-dimensional multimodal modular transport system"*, is answered by the full implementation included in Chapters 3, 4, and 5. The subquestions (listed as SQ1-5) are answered accordingly (1-5).

SQ1. What are the objectives we aim at by optimizing the system mentioned above?
SQ2. Which operational research (OR) models could be the basis of this holistic model?

SQ3. How can such a complicated model be solved effectively?

SQ4. What performance indicators should be applied in the model to measure the operational efficiency of the system?

SQ5. How do intermodality and other distinctive features exert their impact on operational efficiency?

1. The pivot target we aim at in the project is to optimize the overall transport cost in a freight-centric, passenger collaborative transport system (SQ1), and to provide pragmatic operational advice on how to make the most out of the designed system.
2. The operational research models used as the components of the holistic model are Pick-up and Delivery Vehicle Routing Problem (PDVRP) and 3-Dimensional Bin-Packing Problem (3D-BPP). The former one contributes to formulating the vehicle routing part of the model, while the latter is used for checking the feasibility of the routing and packing scheme. Both models are modified to adapt to the demand in solving this problem.
3. In case that both sub-models are NP-hard, and cannot be solved within a reasonable time period, as indicated in section 4.3, we proposed a method to solve the model in two phases. The first step is to solve the PDVRP problem according to the model developed in Chapter 3, and determine the routing scheme of each vehicle. Then, we check the feasibility of the routing plans provided by the results of the previous step. By breaking down the model into two parts, the modelling and computation complexity are both significantly reduced. Moreover, it is also mentioned in the section 4.3 that a small dataset is opted for, to further reduce the computation complexity while maintaining the representativeness of the designed problem instance. Some further work could be done to compress the computational time while not sacrificing the scale of the instance. The recommendations will be proposed in the next section.
4. As is described in the answer to SQ1, one of the main objectives is to explore how to operate the designed system in an efficient manner. To measure the efficiency of the system, we started from decomposing the overall cost into more detailed terms, which are fixed costs such as vehicle usage cost and demand skipping penalty, and variable costs such as travel distance cost, tardiness penalty, and detour penalty. In practice, cost terms could be reverted to the original value, e.g., travel distance in kilometers, or tardiness in minutes, to provide more straightforward analysis. Additionally, the deadheading distance of the vehicles, together with the pods' capacity utilization rate, is also calculated to measure how much of the transportation capacity is wasted. These performance indicators work together to provide a comprehensive understanding of the operational efficiency of the system.
5. In this system, the feature of intermodality is primarily reflected through the capacity of train stations and the departure schedules of trains, which also influence each other. Due to the limited scale of the problem instances used in this study, the capacity of train stations has minimal impact on the solution outcomes. Even when the number of vehicles exceeds the processing capacity of the stations, the routing results indicate that not all vehicles are utilized. To further investigate the effect of this feature on the system's operational efficiency, it would be necessary to use a much larger dataset. The feature of passenger-freight intermodal transport has shown a more pronounced impact in the context of this model. Compared to traditional systems where passenger and freight transport are separated, simulation results indicate that the system designed in this study can reduce deadheading distance by at least 14.7% across most parameter

ranges. This reduction is beneficial for various operational cost factors that were not explicitly demonstrated in this study, such as vehicle maintenance costs and turnover rates. Moreover, reducing empty vehicle trips can also contribute to lowering the overall emissions of the system. Similarly, constrained by the dataset scale, the issue of cargo compatibility was not explored in depth in this study. However, we can still observe the direct impact of introducing incompatible cargo on various cost or penalty terms in the original data.

5.2. Discussion and recommendations for future work

5.2.1. Mathematical modelling

The problem in the mathematical modelling part is mainly caused by the 3D-BPCC part. Because of the dynamic nature of the system, a holistic model integrating routing and packing, which could solve them simultaneously, is excessively difficult to develop, the main difficulty lies in this aspect is that we need to release the space and the coordinates of a newly unloaded cargo, regardless of passenger or freight, dynamically. Thus, to address the problem, we had to adopt the method to solve the routing problem first, and then solve the packing problem by checking if the routing scheme is feasible packing-wise.

There are three options for the future development of the model. One way is to model the two problems as a whole. By treating the problem as a dynamic programming problem, one could try to solve the problem with the rolling horizon approach. Secondly, one could model the two processes separately, and try to combine them in a heuristic algorithm. This was explored during the early stage of the project, and it will be discussed more thoroughly in the follow-up section. The last is to further constrain the model by regulating the sequence of the pick-up and delivery process, which means only allowing delivery after all the demands are picked up from their origin. This measure to simplify the modelling process is least recommended as it goes against the nature of the PDVRP, but nevertheless, it should reduce the complexity of the problem effectively.

5.2.2. Solving method design

This project aims at solving a problem that consists of two NP-hard sub-problems, which means any attempt to solve it with a commercial solver would take a huge amount of computational resources. Early attempts to solve the model with Gurobi with a medium-sized problem instance take more than a day to finish, and as shown in the Figure 4.3, we could see that up to 24 hours time limit, the optimality gap obtained by Gurobi solver was 74.7%, which is generally unacceptable. The reason why the computation speed is slow is that VRP is an NP-hard problem with a computation complexity of $O(n!)$ [43], in which n is the number of customers (i.e., nodes), and PDVRP will be even more difficult to solve with an exact method. With the number of nodes in the problem instance scaling up, the computation time increases exponentially. In this thesis project, using a solver to analyze the model is sufficient; however, it would not be a practically feasible method for solving the modeling in a real operational environment. Thus, solving this model with more advanced methods, such as applying heuristic algorithms, would be a better alternative, as they can reduce the solution time from several hours or days to several minutes.

Several options are viable according to the existing literature, from the basic metaheuristic methods like the ALNS proposed by Ropke and Pisinger in 2006 [50], which integrated a competitive use of sub-heuristics, effectively improving solutions for the Pickup and Delivery Problem. In recent years, there are several combined heuristics algorithms have been proposed in different literature as well[65][89], these carefully designed algorithms can provide almost optimal solutions (usually within 5% optimality gap) within a reasonable computation time.

A simplified prototype ALNS was implemented in the early stage of this project, and we found out that the bin-packing process contributes to the majority of solving time, this is also a point that should be taken extra care of.

For the suggestions on future research, the follow-up researchers could explore a series of different heuristic algorithms. Furthermore, the machine learning method is more and more widely used in developing operators of the heuristic algorithm. The in-depth development of this vertical segment requires deep collaboration between scholars from different backgrounds, and should be an interesting topic to put effort into.

5.2.3. Constraints on operation

This model strictly restricts that each pod can only access each node once, which isn't in full accordance with the operation condition in real life, as this constraint would lead to an outcome of increasing the number of pods to be deployed in daily operation. However, this would be a minor problem as the main research objective is to establish a model that could be applied to describe and optimize the PODs system. But bear in mind that before we head into the publicizing process, the results provided by this thesis demonstrate the model of this system is valid while the solving method is functioning as it is designed to, and reveal some trends on how the system would behave to the changes of different parameters, it doesn't show the superiority of the system. For future research, a comparison between this system and a more traditional transport system would be a good complement. These researches could reason that this novel system holds the advantage over conventional passenger-freight separated transport systems, as the "traditional transport system" we set as a comparison group in Chapter 4, and to provide some insights for all stakeholders participating in the construction and daily operation of it.

Other constraints could be considered in future research, including differentiating the penalty parameters between passengers and freight because passengers and freight receivers naturally perceive the cost of travel time differently. A "priority parameter" can be added to different demands to better simulate a more realistic distribution network. Additionally, regarding the intermodal transfer process, introducing a more specific timetable for the train stations, and considering more detailed transfer processes would help create a more realistic model compared to the identical time intervals introduced in this thesis.

5.2.4. Practical insights

In addition to its methodological contributions, this research offers several practical insights for both operators and policy makers.

Logistics operators may apply the proposed model as a decision-support tool to design more efficient pickup-and-delivery schedules. Operators can use the proposed model to dynamically allocate vehicles and cargo according to real-time capacity and transfer point limitations, maximizing the utilization of multimodal hubs. The bin-packing component suggests that handling staff and planners should strictly implement compatibility checks to prevent safety incidents.

As for the policy makers, how to support the propagate and implementation of this kind of collaborative transport system, from policy aspect, will be a valuable topic to be discussed about. To begin with, investment on the development and implementation of this kind of system needs to be evaluated by powerful stakeholders such as the local government and traffic bureau, as this process is highly costly. Secondly, policy makers need to adopt policy to encourage demand generators to utilize the collaborative transport systems, for example, promoting collaboration between different companies in a same region, or even in different regions, when this system is well-developed and well-spread out. Last but not the least, as we already see in the numerical experiment in this thesis, some parameters in the previous Chapter 4 could greatly affect the propagation of the system. Relevant bereau should carefully evaluate the pricing strategy at the early stage, to promulgate the wide spread of this novel system.

Appendix

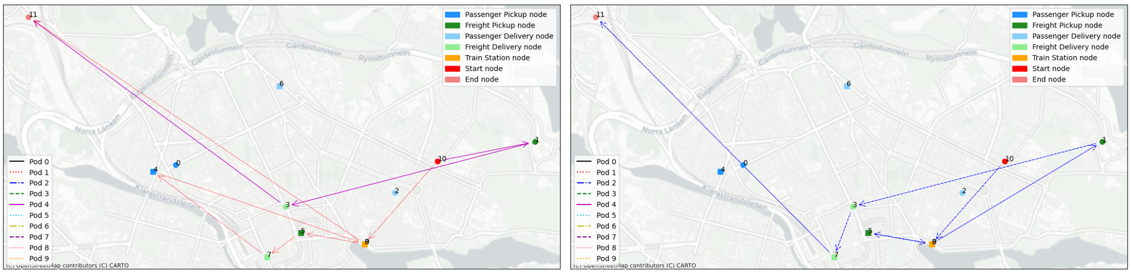

Figure 1: Routing maps-different α_c

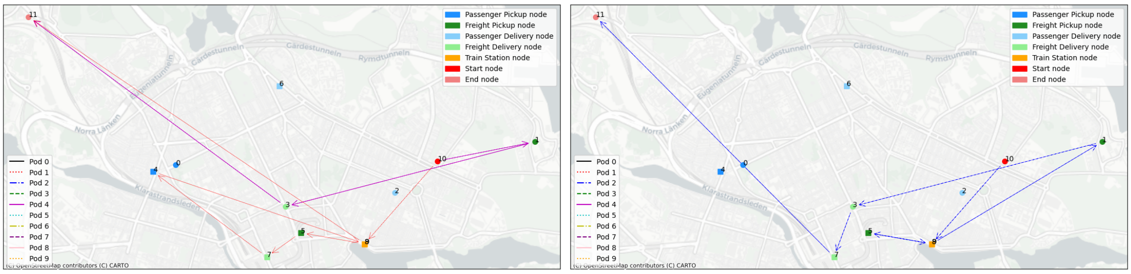

Figure 2: Routing maps - different α_k

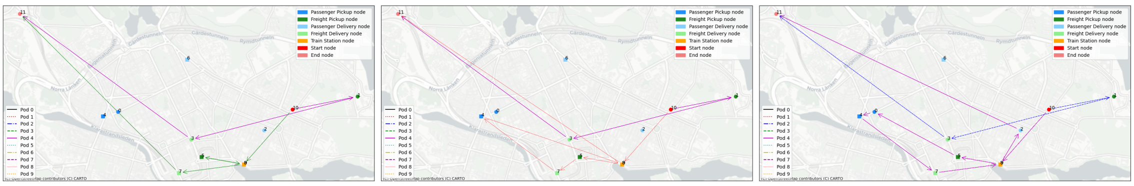

Figure 3: Routing maps - different α_p

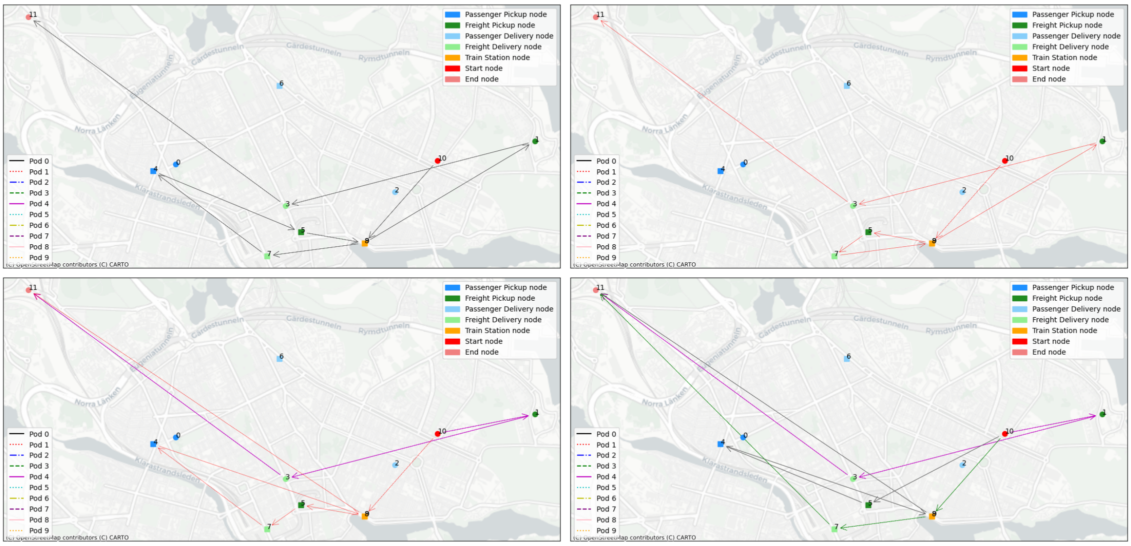

Figure 4: Routing maps - different α_l^f

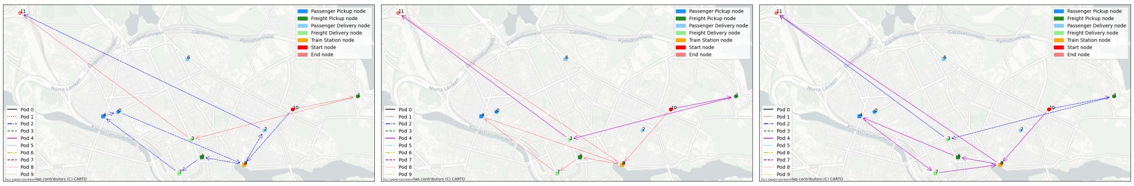

Figure 5: Routing maps - different α_l^p

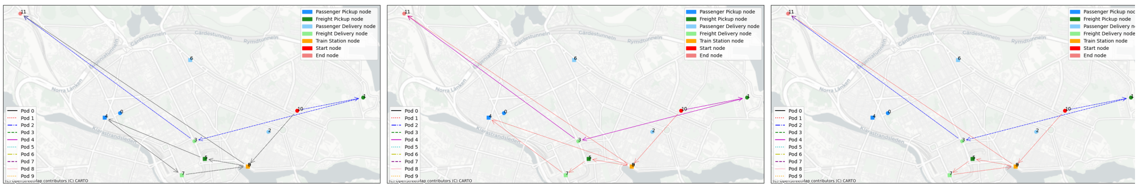

Figure 6: Routing maps - different α_o^f

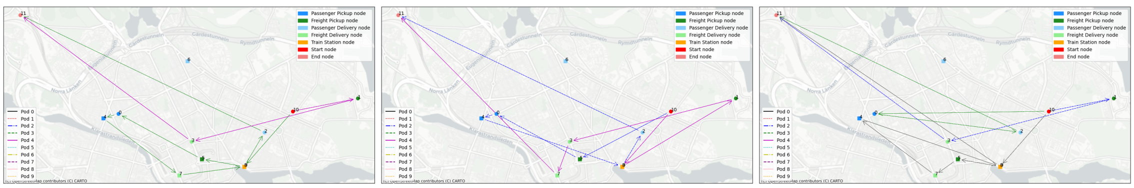

Figure 7: Routing maps - different α_o^p

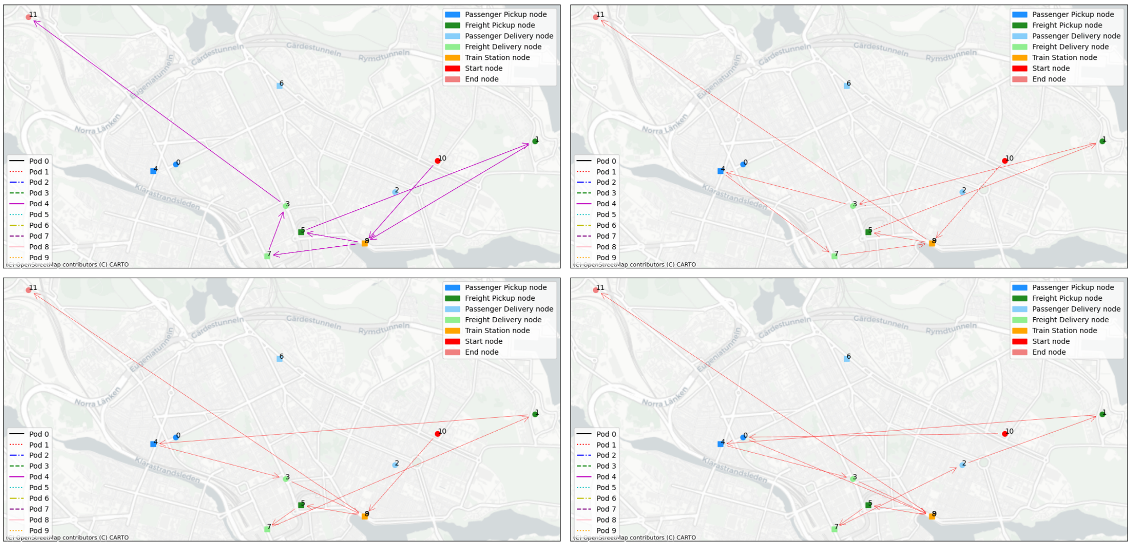

Figure 8: Routing maps - different v_{pod}

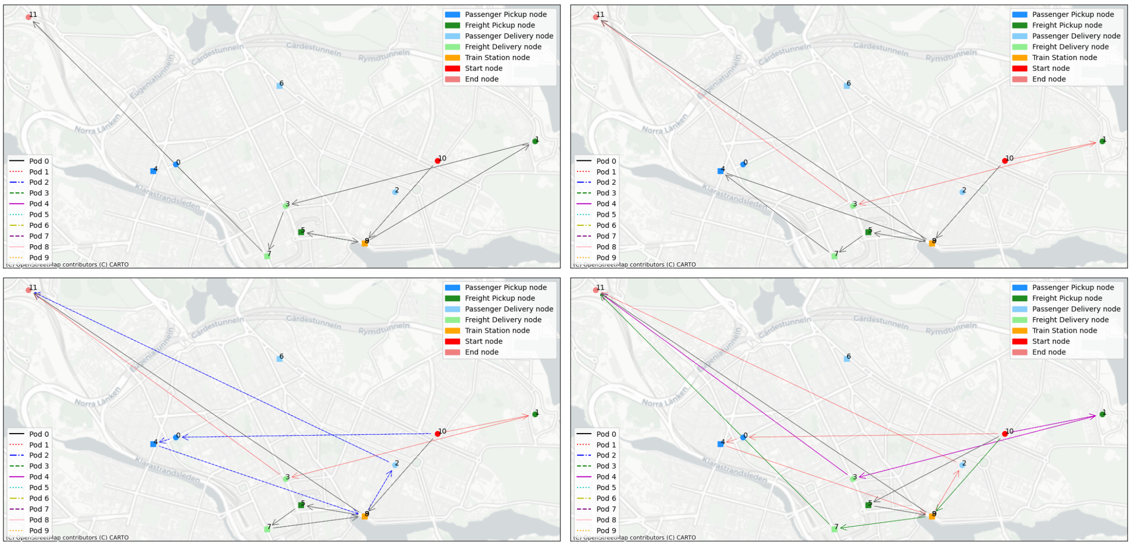

Figure 9: Routing maps - different number of pods available

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Designing a Freight-Centric Integrated Passenger-Freight Transportation System with Routing and Bin-Packing Constraints

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Abstract

This article presents a mathematical model for a freight-originated pickup-and-delivery routing problem (PDVRP) while considering the 3-dimensional bin packing constraints with compatibility issue (3D-BPCC), and the transfer interface between road and rail transport.

In this article, the train station's handling capacity and its impact on routing decisions is considered. Second, the compatibility issue between different kinds of cargo was integrated into the bin-packing model. By solving the PDVRP and the 3D-BPCC sequentially, the computation complexity is greatly reduced while maintaining the relative reliability of the results. Furthermore, a comparison between the routing results and objective function value of the newly proposed PODs system and two traditional freight/passenger separated systems is carried out.

Solving the model by Gurobi, a series of sensitivity analyses are carried out to determine how changes in different penalty coefficients would impact the system behavior. The optimization results are then compared to the two traditional transport systems, and analyses of the pros and cons of the PODs system are conducted. The results show that the PODs system holds an advantage in terms of total cost in most parameter ranges, and this advantage is mainly due to shorter travel distances.

Keywords: Integrated Passenger-Freight Transport (IPFT), Pickup and Delivery Vehicle Routing Problem (PDVRP), 3-Dimensional Bin Packing Problem (3D-BPP)

1. Introduction

Environmental problems caused by freight and passenger transportation have long been an extensively posing threat. According to United Nations (UN)[1], in 2021 around 23% of total greenhouse gas (GHG) emissions across the world originates from road passenger and freight transport, while road transport also consists of 76% of overall transport emission in EU region[2], this figure shows conflicts with EU's target in environment aspect stated in European Green Deal: a net-zero carbon emission by the year 2050.

To address this problem, the EU is advocating a mode shift process in the transportation realm. In the conceptual design phase of new transportation means, some critical operational issues are faced by the designers.

For passenger transportation, the occupancy rate of current fixed schedules of public transport in industrialized countries is rather low. For cargo transportation, the booming of e-commerce necessitates more freight delivery services within urban areas, while this would lead to a worse situation in terms of congestion and pollution. What's more, although the EU is not suffering from an immediate long-haul truck driver shortage problem as what is happening in the United States, a foreseeable driver shortage would still happen due to the retirement of a relatively large portion of bus, coach, truck and train drivers in next decade while there are not enough apprentice workers in the same industry[3].

Various transportation solutions have been explored in order to tackle these challenges. Amongst all the early exploration by transport solution providers, a novel transport system that contains the following features: automation, on-demand transport, integrated freight-passenger transportation, multimodality and co-modality is fairly reasonable. Moreover, as a large portion of long-haul maritime and road transportation demand is filled by containers, the huge success and the convenience for loading and unloading provided by the standardized, modular system are not to be neglected.

Based on these existing solutions and the knowledge learned, an assumption could be made that a system which could consolidate the freight and passenger demand altogether, a novel transportation system of which compatible the all the features above could potentially enhance the efficiency of the transportation system, and a modular vehicle system would be a good answer which provides solution to most features demanded.

According to the conceptual framework designed based on the demand proposed by the industry, and also to draw solutions to mitigate the challenges above, an automated modular collaborative transport equipment which could operate in different infrastructure systems could potentially enhance the efficiency of existing transport solution and could be a good answer which provides solution to most of the features demanded.

Given the knowledge provided by the predecessors, currently there are several companies (Rinspeed[4], Renault[5], Mercedes[6], etc.) providing such modular vehicle system solution. On the other hand, the public transit system in many cities all over the world is devoted to deeper and deeper electrification, this proves that electrification is an inevitable and irreversible trend. Based on the requirements proposed above, a transportation system which consists the character of standardized carriers, combining passenger and cargo transportation together, with carriages could be operated on both rail and road, providing flexibility in transportation capacity for both passenger and cargo and a capability of providing door-to-door service could be a decent system to address the problems stated above.

Modular design principles have emerged as a pivotal paradigm in the automotive industry, offering a myriad of benefits for both passenger and freight vehicles. This paper presents a thorough examination of the necessity and superiority of modular passenger and freight vehicles, focusing on their flexibility, resource optimization, environmental sustainability, adaptability to future technological developments, and cost-effectiveness.

To achieve the target of efficient operation of such a futuristic and potential system, optimization of route planning, minimizing empty cargo spaces, and other modular-based enhancements contribute to a more cost-effective and streamlined transportation system is a fundamental process. Amongst the aspects just stated, this thesis would mainly focus on throwing light on the following unexplored context: A pickup and delivery vehicle routing problem (PDVRP, or VRP-SPD) combined with multimodal transport context (but only focus on intermodal), integrated passenger-freight transport and heterogeneous demand consolidation of modular vehicles. The author hopes the research results will not only be helpful in giving insights on the specific aforementioned pod transit system, but also provide a solid basis for the construction of a modular vehicle system, including supporting infrastructure and service network design.

2. Literature review

This study builds upon a specialized version of the Pickup-and-Delivery Vehicle Routing Problem (PDVRP), extending it to address challenges in integrated passenger-freight transport and modular multimodal systems. While the classical VRP, proposed by Dantzig and Ramser in 1959[7], has been extensively developed, the PDVRP variant—introduced by Desrochers et al.[8] and Savelsbergh and Sol[9]—adds complexity by allowing on-route pickups and deliveries under constraints such as time windows and vehicle capacities. Comparing to the classical PDVRP model, our model distinguishes itself by incorporating collaborative transport and synchronization with railway schedules. While some of these elements have been individually addressed in prior works, their integration remains underexplored.

For the core part of the model, although there is no identical background setup, several existing operational research problem categories are similar to our context, which indeed gave us inspiration for detailed model construction.

Relevant extensions of PDVRP include the Container Drayage Problem (CDP)[10][11][12] and Dial-a-Ride Problem (DARP)[13], both related but limited in capturing intermodality or mixed demand types. On the basis of the latter, the Share-a-Ride Problem (SARP), proposed by Li et al. [14], is closer to the demand of this problem context in spirit, combining passengers and freight, but it omits intermodal transfer points and network-wide coordination.

Routing problem in multimodal, integrated passenger-freight transport is the most researched section for all the variants of PDVRP, varieties of models and corresponding algorithms are proposed over studies carried out in past decades. PDVRP in the multimodal transport section is highly based on the basic model, by adding multiple constraints, the model can adapt to different detailed contexts easily, according to its high compatibility and extensive nature. Research in this section also has multiple focal points due to the differences in the researchers' professions. Most recent work carried out in this area focuses on algorithm optimization, while the minorities have concentrated on facility location planning, service network planning, network resilience analysis, etc.

The number of studies on PDP with a multimodal background has ushered rapid growth since 2012, most of the relevant literature in the early years didn't introduce the modal of freight-sharing carriage capacity with passengers but only share infrastructure. In the context of this project, we not only aim at carriers sharing the same infrastructure system but also passengers and freight sharing the same capacity in a carrier. Although the number of studies related to the integration of passenger and freight transportation increased after it was proposed, when we scope down to those who have introduced a passenger-freight integrated transport system with a multimodal background, the number of literature is rather few, and as for those literature which discussed the interface between different modalities is even less.

Although the total number of relevant literature is few, multiple interesting literature still provided insight on integrated passenger and freight transport published in recent decades, most of which are urban scenario-based, while some of them included the combination with railway transport (including long haul railway service and subway)[15][16][17][18][19][20].

The majority of these studies are dedicated to the combination of passenger and freight transport in existing urban PT systems, for example, subway and bus networks[21][22][23], they provided some exquisite techniques for solving a PDP with basic service network, but this is not the case for our research, where there is no basic service network existing.

The research with the most similar background to this project is [24] conducted by Li et al., this research extended the application scenario of research conducted by Ghilas et al. and Masson et al.[25] to a transport system with multimodal background, it discussed the dynamic passenger flow constraints and the scheduled line operation constraints, but the road segment services in this research are provided by dedicated freight vehicles, on the contrary, the transport system to be researched in this project will provide a comprehensive freight-passenger transport service all across the network.

Research in this section is thorough and detailed, yet there are only very few research studies infusing modular vehicles in PDVRP. This is mainly because the modular vehicle is a new feature binding with multimodal transport. Even if the scope of this thesis project is not to look into the detailed operation of this system, we will nevertheless take the interface between road and rail segments into consideration. This would be one of the main research gaps to be filled and an innovative point of this thesis.

Research on modular vehicle routing remains sparse due to the concept's novelty, as the projects regarding modern modular vehicles haven't been proposed much until 2015. Existing works mostly explore the feasibility of modular vehicle platooning and how they could enhance transport efficiency[26][27], but often lack quantitative modeling or overlook passenger-freight collaborative transport. Despite the limited number of studies conducted, there are still several studies regarding the routing problem of modular vehicle. Pei et al.[28] found that a modular fleet with platooning feature could reduce the overall cost noticeably compared to a traditional shuttle bus system. This is a pioneering research conducted in this area, but it doesn't include the feature of collaborative transport of passenger and freight demand, while it also didn't consider intermodality. The advantage of a modular transit system comparing with traditional transit services under different scenarios was further proven by other research like [29][30][31]. Collaborative transport was a less-studied sector. Lin et al.[32] proposed a system with two transport modalities that integrated passenger and freight transport, the vehicles could also be merged into platoons and split whenever needed. The authors suggested the high potential of modular, integrated transport systems regarding their efficiency, but their discussion lacks support for quantitative analysis or any real cases. Intermodal transition or infrastructure interaction were also discussed by very few, which are main gaps to be filled by this research.

Demand consolidation, especially under heterogeneous cargo compatibility, has been more thoroughly addressed. demand consolidation problem originates from the demand for solutions for two different problems. The first one is the demand for finding a maximum utilization rate for cargo carrier capacity, the other one is transportation risk management, mainly focuses on freight flow management, isolating hazardous materials according to their characteristics. In this project, the main focal point is the former one and there are some recent research incorporated on heterogeneous demand consolidation. Notable works include Bortfeldt Homberger's two-stage VRLP approach[33] and Meliani et al.'s integration of 3D bin packing with heterogeneous fleet routing[34]. Liu and Zhao in 2019[35] proposed a mixed integer programming model combining cargo consolidation with routing decisions to minimize one-time costs for selecting the subset of vehicles and total operation costs. This model is based on their cargo flow prediction model developed based on the traffic assignment 4-stage model. But this research, together with the one conducted by Cortes and Suzuki[36], both neglected the possibility that there is always a compatibility problem between different kinds of cargo. Nevertheless, [36] is one of the rare ones considering freight demand consolidation at the departure node in most of the existing literature, shipment consolidation is only considered in median nodes including cross- docks[37][38][39][40] or consolidation/distribution center[41] in the network. However, these models often overlook compatibility constraints or fail to include routing considerations. Recent work on bin packing with compatible categories (BPCC), such as Santos et al.[42] and Tsao et al.[43], these studies are more algorithm-based, and, although they provided valuable insight into the modeling of bin packing problems with compatible categories, they haven't included routing decision.

Among the PDVRP-related literature, the least attached characteristic is the heterogeneity of the time window for different types of nodes, as none of the existing research in relevant areas draws attention to this feature. Another aspect which hasn't been thoroughly explored is the synchronization with the PT operation schedule, although Pei et al.[28] included the PT system schedule.

This study aims to bridge these gaps by proposing a unified model that integrates modular vehicle routing, intermodal transitions, passenger-freight collaborative transport, and heterogeneous demand compatibility—elements that have mostly been treated in isolation in the existing literature.

3. Problem statement and model formulation

The transport system modeled in this article is a variant of the system that is used in the pick-up and delivery problem, as is roughly demonstrated in the following Figure 1. The vehicles (named as pods in the following parts) utilized in the system can be used for transporting freight cargo and passengers, the two parts can be concurrently put in the same pod as long as the cargo items do not react with one another in a potentially harmful way, or the items are suitable to be put together with passengers.

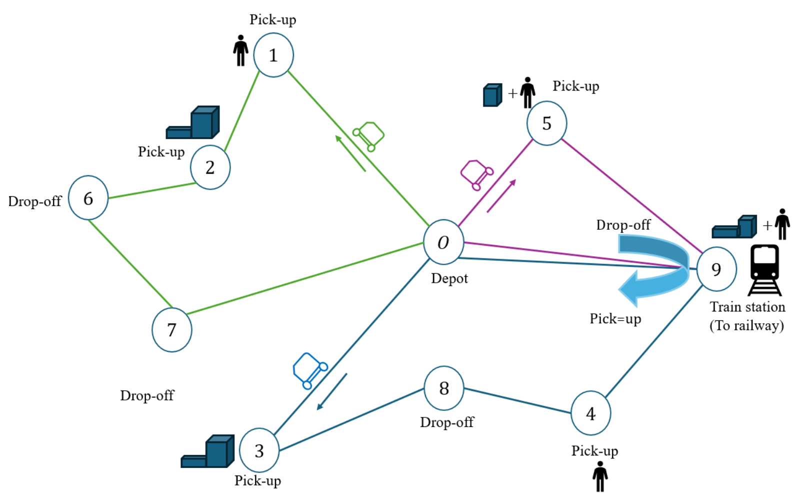

Figure 1: System schematic diagram

The optimization model representing this system is composed of 2 different decision processes, which are the packing decision and the routing decision. These two decisions will be made sequentially, by first solving the routing problem, then checking the feasibility of the packing problem. If the packing scheme is feasible, the current routing scheme will be retained and record the value of the objective function as well as all the penalty components for sensitivity analysis carried out in Chapter 4. If the packing scheme is infeasible, we will adhere to the results provided by the bin-packing model regarding how many additional pods will be necessary to meet all the demands specified in the routing plan, and calculate the cost of deploying extra vehicles. This extra cost will be added to the objective function.

A flow diagram regarding how the model integration is implemented in this section is shown in Figure 2.

The PDVRP is defined on an undirected complete graph $G(N, A)$ over an operation time horizon $[0,\ T_k]$. N is the set of all nodes. In the road network, a train station

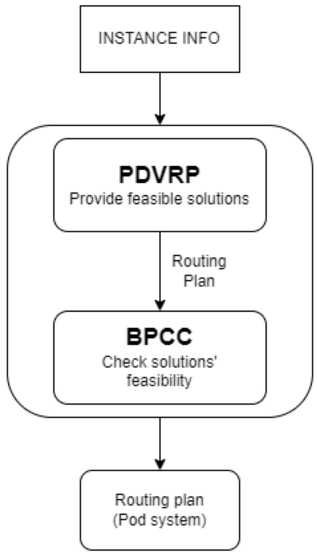

Figure 2: Routing and packing model integration

T exists. Some of the demands in the network will be transported to T, while T will also generate a certain number of demands to be transported to other drop-off nodes. Considering that train stations have an upper bound of handling capability, a capacity value for the train station is introduced. This capacity value limits the number of pods that can access the train station within a specified time interval. The pods are free to access train station nodes as long as the capacity is not exceeded, then they go back onto the road network, carry out services, and finally end their service trips at the ending depot.

Several assumptions are made before the model is formulated:

1. Passengers and freight are always ready for pickup at the expected arrival time.
2. One freight unit takes up as much capacity as one passenger and has the same average dwell time.
3. The pods have homogeneous specifications.
4. The travel time between nodes solely depends on the distance between nodes and the travel speed of the pods.
5. The train station nodes have a limited capacity of serving pods.
6. All pods start their services from the same starting depot and end their services at the same ending depot.
7. All the freight demands need to be served, passenger demands can be skipped with a certain amount of penalty.
8. Each demand, regardless of passenger or freight, is treated as a cuboid with a specific geometric dimension and mass.

9. All the demand at the same node to be picked up is non-splittable, which means, the demand at one pick-up node is either carried by one pod or is completely skipped.
10. The rotation scheme of how the demands are packed in the pod is not considered in this research.

These assumptions make sure that the model in the following sections can cover all the main aspects we wish to explore without making it too complicated and unsolvable. The full mathematical model is listed and explained in Appendix B.

4. Case study

4.1. Instance introduction

The problem instance used for sensitivity analysis is mainly based on the dataset used in [18]. For the sake of computational convenience, a subset including 12 nodes is randomly chosen to be applied in the analysis in the next sections. The distribution of the nodes in the designed problem instance on the map is shown in Figure 3, the background map is loaded from OpenStreetMap.

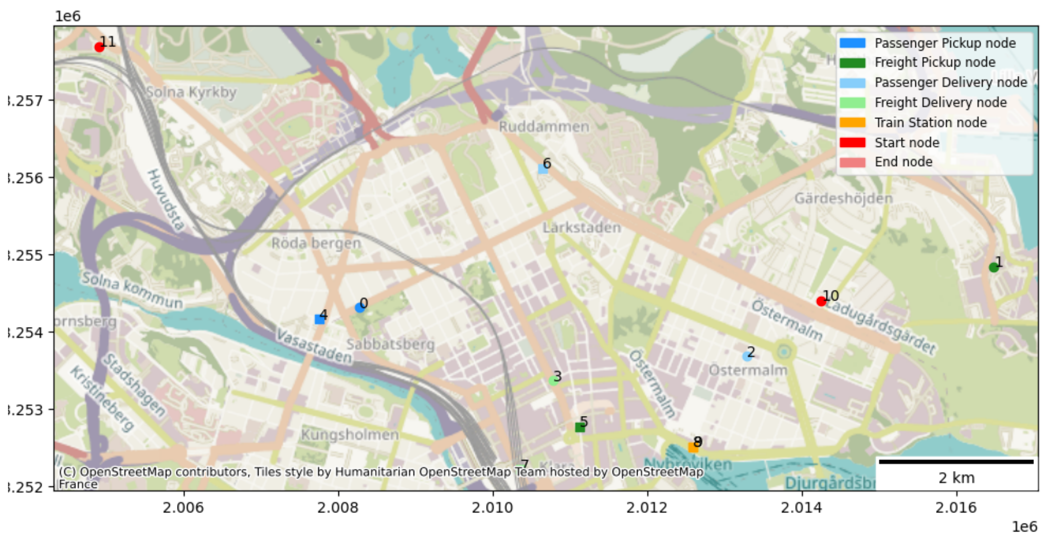

Figure 3: Network geographical setup

The categories of the items and a compatibility matrix are also randomly generated, as shown in the Table C.1 in Appendix C.

To measure the optimality of the POD system, a traditional transport system serving freight and passenger demands separately is also introduced as a benchmark. This traditional transport system consists of two parts: a "Private car" system responsible for passenger demand transportation and a "Vans" system responsible for freight demand transportation. The basic model for solving the routing problem for these two systems will be almost the same as what we proposed above. For the two traditional transport systems, the detour problem will not be considered, and skipping demand nodes is forbidden, as they are dedicated transport systems. For every parameter setup examined in the sensitivity analysis carried out in this section, a comparison between the objective function value of both PODs system and the two traditional systems will be carried out, as well as their combination. A flow chart demonstrating this comparison and evaluation process is shown as the following Figure 4.

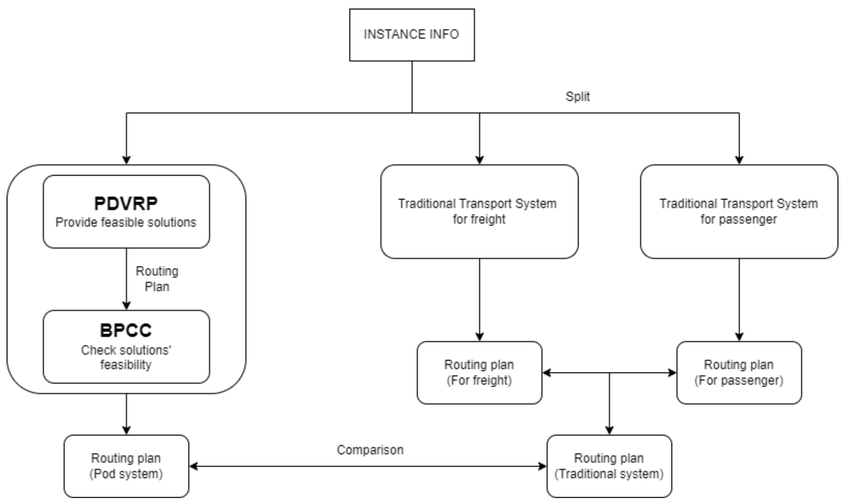

Figure 4: Comparison model across different systems

The parameters applied in the case study are listed in the following Table D.2 in Appendix D.

4.2. Sensitivity analysis

The sensitivity analysis carried out around different parameters presents the result as expected. The PODs system hold an advantage in terms of total cost in most parameter setups. From the sensitivity analysis, the reasons for the lower cost of the PODs system are the following: shorter travel distance, the flexibility to skip passenger demands, and the

As an example, the following Figure 5 demonstrates how the total travel distance of vehicles in different transport system changes with the variation of α_c. The total travel distance of the PODs system stays well below that of the two traditional systems combined. Although this is achieved in exchange of skipping serving 1 or 2 demand nodes in the network, the total cost of the PODs system stays lower most of the time.

Among all the performance indicators, the total travel distance traversed by all the pods stays lower than that of both traditional transport systems combined in most cases. Only in some extreme parameter setups, the total travel distance of the PODs system

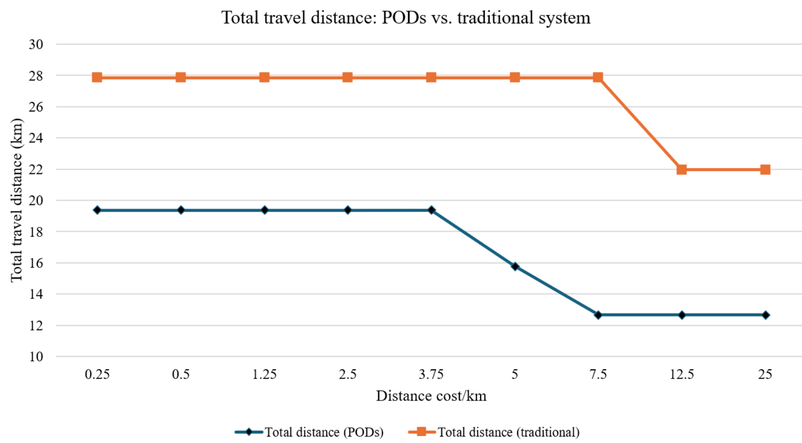

Figure 5: Changing trend of total travel distance with the change of α_c

would be higher than that of the traditional system. For example, when α_p is significantly higher than other coefficients in the objective function, and the number of available pod is close to the number of OD pairs. This trend follows the experimental results in [26][27]. Particularly, compared to traditional systems where passenger and freight transport are separated, simulation results indicate that the system designed in this study can reduce deadheading distance by at least 14.7% across most parameter ranges. This reduction is beneficial for various operational cost factors that were not explicitly demonstrated in this study, such as vehicle maintenance costs and turnover rates. Moreover, reducing empty vehicle trips can also contribute to lowering the overall emissions of the system.

Apart from the shorter travel distance, the number of pods used to provide passenger-freight collaborative pickup and delivery services is also less than the number of vehicles required to carry out passenger and freight delivery services independently, under the same parameter settings.

The sensitivity of the other parameters will be discussed in the following sub-sections.

4.2.1. Demand skipping penalty

By adjusting the value of α_p, the total travel distance of the pod increases sequentially, and the freight detour penalty follows the same trend. However, the passenger tardiness penalty shows a significant increase in the final phase, indirectly explaining why passenger demand at node 0 is consistently skipped when α_p is relatively low.

The total cost of the PODs system is lower than that of the traditional system in the first two phases, but it incurs a higher total cost in the third phase when α_p is large. This indicates that under the current system configuration, if there is a high demand for LoS (level of service) or if there are high-priority, non-skippable freight or passenger demands in the network, the cost of using the traditional transportation system would be slightly lower than that of the PODs system. The higher cost is also triggered by the incompatibility of freight boarding from node 5 and passenger, which will lead to one more pod being

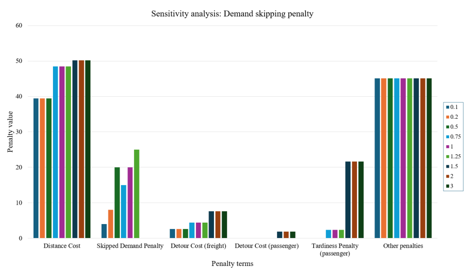

Figure 6: Penalty values when α_p changes

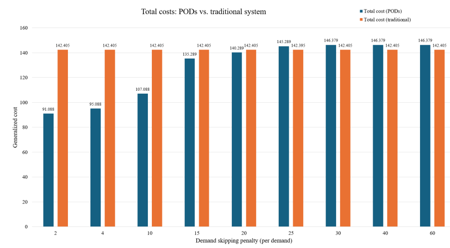

Figure 7: Total cost comparison: PODs and traditional system

deployed. In a more complicated network, this deficit can be much more obvious.

4.2.2. Pod usage penalty

When α_k stands between 2 and 30, the routing result of the system is completely unaffected. When $\alpha_k \geq 40$, there is a drop in the number of pods deployed for pickup and delivery tasks. This is because the decrease of pod usage cost offsets the increase in demand skipping penalty. Further decreasing the number of pods to 1, the detour and tardiness penalty increases, the latter of which is significant. Node 1 contributes most of the increase in the freight tardiness penalty, which is in accordance with the conclusion in the previous section.

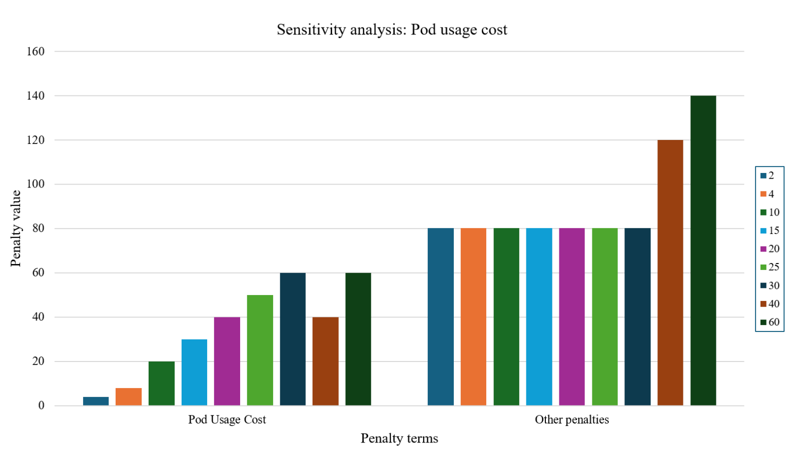

Figure 8: Penalty values when α_k changes

For comparison, traditional transport systems indicate similar patterns. The only difference is that the private cars which serve the passenger demands, only 2 cars are deployed when α_k is low. With one car in service, the total travel distance decreased by 31.8%, but the passenger tardiness penalty grows significantly. Overall, the PODs system performs better in terms of total travel distance, so as the deadheading distance. In terms of tardiness, the PODs system holds an advantage under most of the α_k values, but when this parameter takes a large value, the traditional systems have smaller maximum and average tardiness values.

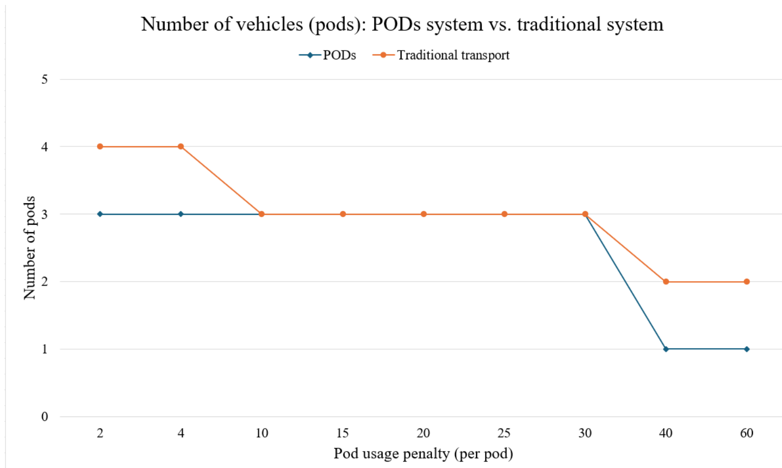

Figure 9: Number of pods used in two systems

In conclusion, the objective function is not sensitive to the changes of the parameter α_k. The low sensitivity of this parameter is mainly caused by a relatively high travel distance penalty.

4.2.3. Detour penalty

Under the current road network configuration, the system's routing behavior is highly insensitive to changes in the detour penalty coefficient, the reason could be that the detour penalties only contribute to so little portion of the total objective function, that changes to the parameters α_o^p and α_o^f should be very drastic to see the impact on the result. Further experiments reveal that the detour penalty primarily competes with the tardiness penalty. When either α_o^f or α_o^p is high enough, pods will prioritize the "theoretically shortest" route between pick-up and corresponding delivery node pairs, even if these routes result in significantly higher tardiness penalties.

When α_o^p stays in the range of [0.01, 0.5], the passenger detour penalty changes linearly, while the routing solution of the PODs system remains unchanged. However, further increasing the value of α_o^p exceeds five times its initial value, the system, now able to change the routing plan and deploy more pods. With α_o^p values approaching those of α_l^p and α_c, the system would accept a longer total travel distance in exchange for lower time-related penalties. In the case where α_o^p is equal to α_l^p, the passenger detour penalty is reduced to zero, and the tardiness penalty decreases by 37%. But overall, the system is still relatively insensitive to the changes in the parameter α_o^p.

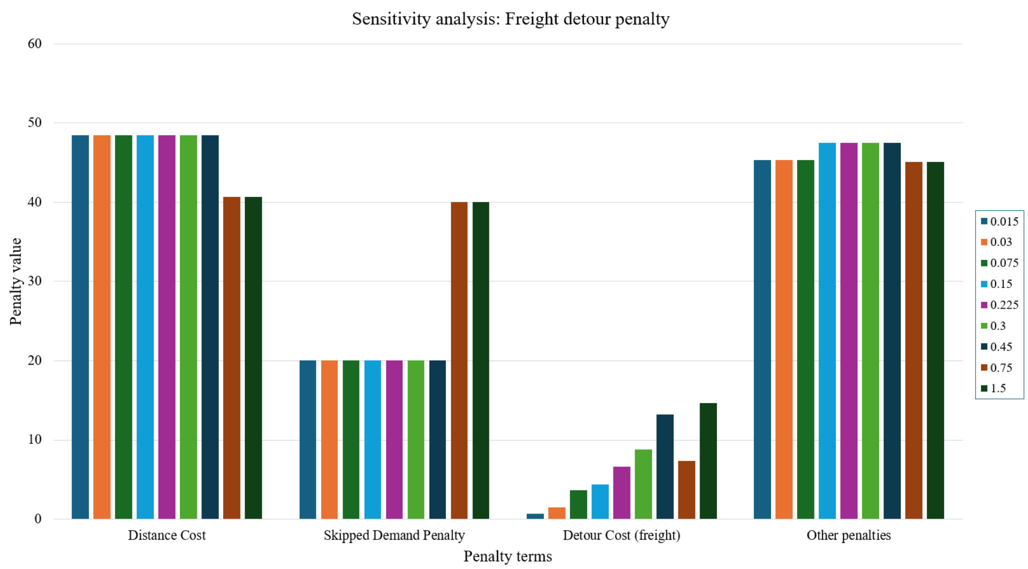

Figure 10: Penalty values when α_o^f changes

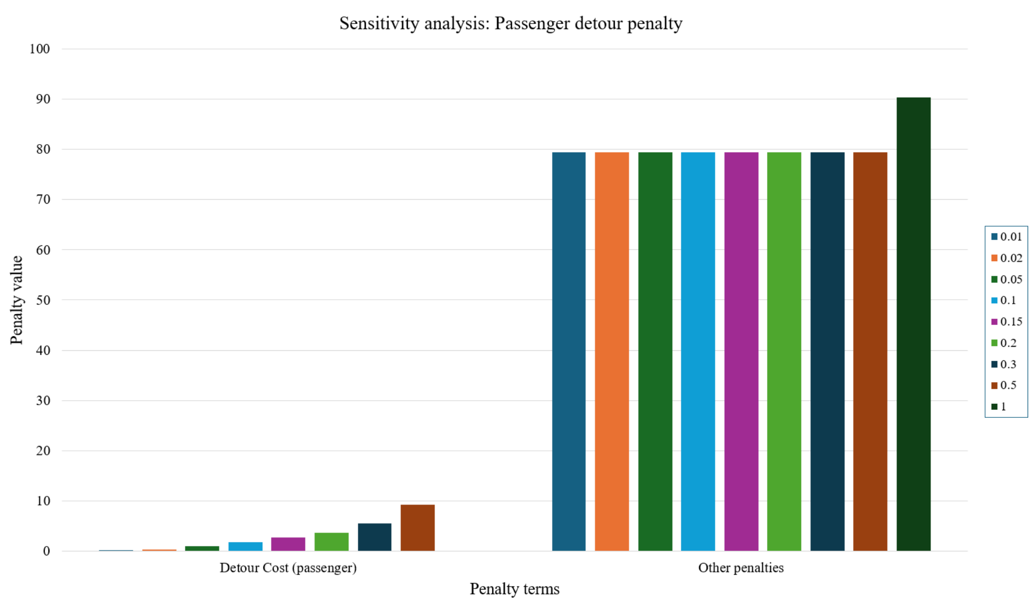

Figure 11: Penalty values when α_o^p changes

4.2.4. Tardiness penalty

From the overall experimental results, the system demonstrates low sensitivity to changes in tardiness-related coefficients across most of the tested range.

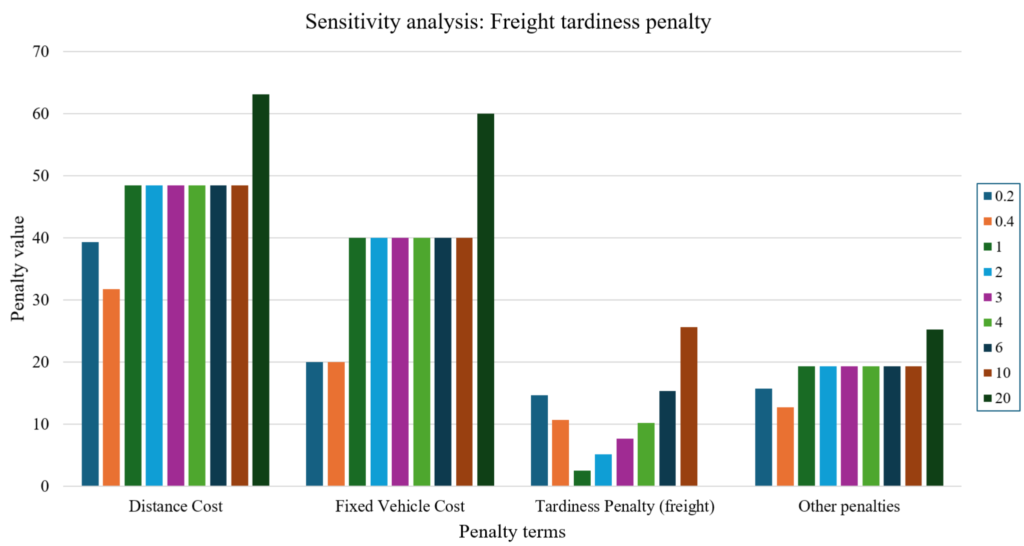

Figure 12: Penalty values when α_l^f changes

In the low range of α_l^f (0.2-0.4), relatively higher delays are still acceptable to the system as a whole. During this stage, the tardiness penalty accounts for approximately 10%–16% of the total cost. The system utilizes only one vehicle to fulfill as many transportation demands as possible. With the increase of the α_l^f, the system would skip more passenger demands to minimize the tardiness of freight demands, while the freight detour penalty remains at a low level, equal to 1% of the total cost. The system's optimal solution remains stable within the range of 1–10 for α_l^f. When α_l^f reaches 10 times its initial value or higher, the system deploys three vehicles to transport three different freight demands separately to reduce all the freight tardiness to zero.

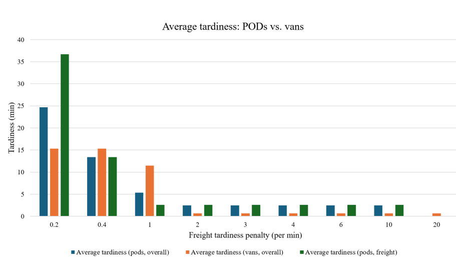

Figure 13: Average tardiness: pods vs. vans

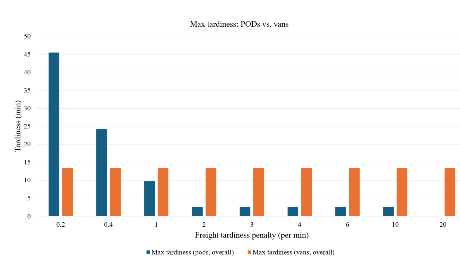

Figure 14: Maximum tardiness: pods vs. vans

In contrast, the traditional transportation system is unaffected by changes in α_l^f. Consequently, the tardiness at each node for fulfilling freight transportation demands remains constant. In the range of small α_l^f values (0.2–0.4), the traditional transportation system shows an advantage in terms of delay duration. Even when $\alpha_l^f > 1$, vans still exhibit a significant advantage in average tardiness compared to the PODs system. The total cost advantage of the vans system mainly stems from shorter travel distances and fewer tardiness minutes. However, when passenger transportation tasks handled by private cars are considered, the PODs system consistently outperforms the traditional transportation system.

For α_l^p, the sensitivity analysis reveals a similar trend to that observed for α_l^f, with the key difference being that the system is less sensitive to changes in α_l^p under the current configuration.

Overall, regardless of the value of the passenger tardiness penalty coefficient, the PODs system consistently holds an advantage in total cost, with the advantage becoming more pronounced as α_l increases.

4.2.5. Average travel speed

The average travel speed (v_{pod}) directly impacts the travel time of pods between nodes. During the variation of v_{pod}, all penalty components, except for the passenger detour penalty, showed significant changes.

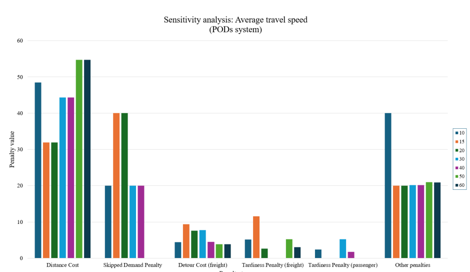

Figure 15: Objective function value under different average travel speed

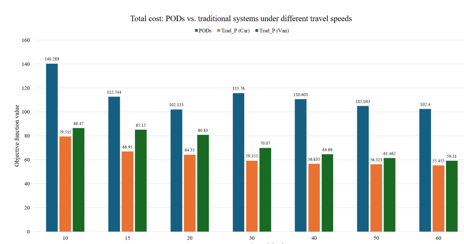

Figure 16: Comparison: PODs system vs. traditional systems

For penalty components other than the tardiness penalty, it is observed that, with a consistent number of vehicles, the average delay time of pods across all visited nodes generally decreases. The only exception is when the average travel speed is 30 km/h, where both the average delay time and the maximum delay at a single node significantly increase compared to the surrounding values.

The combined cost disadvantage of traditional passenger and freight systems, especially at lower average speeds, is primarily due to the need to separately transport passengers and freight. This results in additional vehicles and travel distances. The total travel distance of traditional systems can be up to 72.84% greater than that of the PODs system. However, as the number of vehicles and visited nodes stabilizes, the difference decreases with increasing average speed, eventually stabilizing at around 3%. At higher average speeds, the difference in objective function values between the two systems is primarily due to the additional cost of using one more vehicle.

4.2.6. Number of pods

The number of available pods in the initial settings was set to 5. In the current system network configuration, this number is sufficient to meet all transport demands. In other words, the additional costs associated with using more vehicles, including extra travel distance and the cost of using an additional pod, cannot be offset by better performance in terms of time.

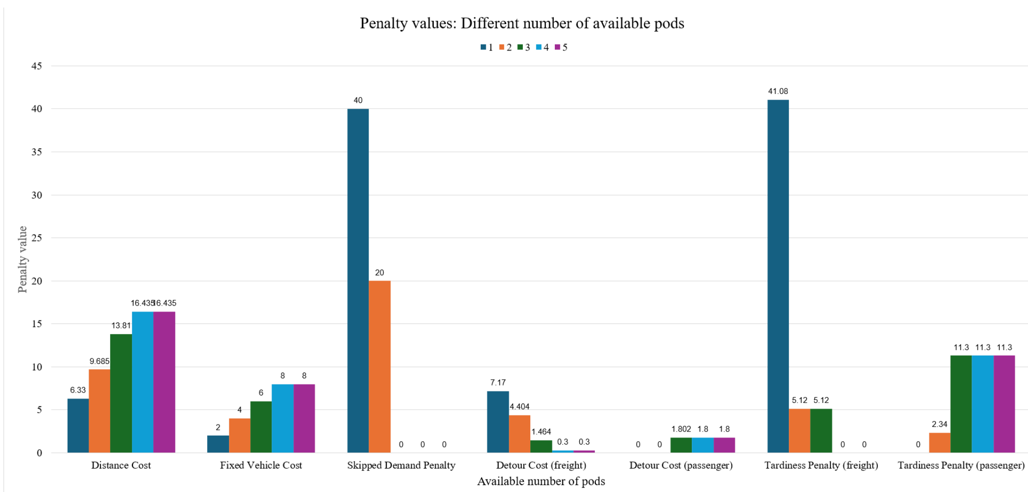

Figure 17: Penalty values' changes under different available number of pods

When the number of available pods is low, the demand skipping penalty constitutes the majority of the total cost. Specifically, when only 1 pod is available, the tardiness penalty for freight demands is also significantly high. Notably, node 1 accounts for 87.5% of the total tardiness in this scenario. The reasons for this significant tardiness at node 1 have already been analyzed in the section on travel distance penalty. This also explains why, when sufficient vehicles are available, the system prioritizes assigning a single pod to handle the 1-3 OD pair demand. Additionally, while the system consistently incurs detour and tardiness penalties when meeting passenger demands, the penalties for freight demands continuously decrease as the number of available pods increases.

4.3. Discussion

According to the results above, it is evident that across most parameter ranges, the collaborative transport system demonstrates a cost advantage over the two representative traditional transport systems selected for comparison. Under the scenarios we established, the PODs system is shown to be worth promoting and has broad application prospects. The primary advantages of the PODs system over traditional systems lie in its use of fewer vehicles, which not only results in a lower pod usage penalty but also leads to shorter total travel distances and reduced deadheading distances. However, it is important to note that the experimental conditions in this study do not fully represent the operational conditions of real-world systems. There is significant room for optimization, both in the parameter values themselves and in addressing factors not accounted for in the current model.

The findings highlight that parameters such as α_c and α_p have a significant impact on the system's routing decisions. For other parameters to have a more pronounced influence on routing, they generally require the combined effect of these two key parameters.

In MILP problems, interactions between parameters are inevitable. For instance, as shown in the section on the pod usage penalty, the influence of α_k alone on the model's routing outcomes is limited, particularly under the current settings of other parameters. However, when α_c is reduced to smaller values, subsequent adjustments to α_k show a much greater impact on routing results. Considering that the value of the total travel distance is significantly larger than other variables, such interactions are predictable.

In future model optimization efforts, the distance penalty should be prioritized, followed by the pod usage penalty and tardiness penalty. The former typically has a higher unit cost, varies when the vehicle changes, and significantly influences the model's outcomes, while the latter requires detailed discussions tailored to different passenger and freight categories, adding to the complexity of optimization.

5. Conclusion

This research addresses real-world challenges in transport systems, such as low public transport utilization rate, increasing demand for green logistics, and the development of modular transport carriers. To better reflect practical complexities and to fill the gap in this specific research area, a hybrid model integrating the pickup and delivery vehicle routing problem (PDVRP) with three-dimensional bin packing (3D-BPP) is proposed under a collaborative passenger-freight and intermodal transport framework.

A mathematical model was formulated to capture key constraints and interactions within such a system, including cargo compatibility, vehicle routing requirements, and intermodal coordination. The model is validated on synthetic datasets by Gurobi, confirming the effectiveness of the model. The simulation process and the subsequent sensitivity analysis provided three main insights. Firstly, integrating passenger and freight flows introduces operational synergies that reduce total system costs. Secondly, the routing behaviour of the PODs system show that more efficient capacity utilization contributes the most to the cost reduction of the total cost. Thirdly, the model remains effective under varied demand and parameter settings, indicating strong adaptability.

These findings support the case for exploring integrated, modular, and intermodal urban transport systems as a pathway toward more efficient and sustainable mobility. The proposed system demonstrated flexibility in responding to varying user demands and operational constraints. Comparative evaluations also showed that the modular pod-based transport system outperforms traditional separate passenger and freight transport modes in most scenarios. Future research could further refine the model by incorporating dynamic demand, energy constraints, and real-time routing updates, thus enhancing its applicability in smart city environments.

Appendix A. List of notations

Table A.1: List of notations

Notation	Description
Indices	
i, j	Indices for nodes
k, m	Indices for pods
v, w	Indices for individual items
r, s	Indices for cargo types
Sets	
N	Set of all nodes, $N = P \cup D \cup T \cup O$
O	Set of depots, $O = O_s \cup O_e$
P	Set of all pick-up nodes, $P = P^p \cup P^f = \{1, 2, \ldots, n\}$
P^p	Set of all passenger pick-up nodes
P^f	Set of all freight pick-up nodes
P^t	Set of all pick-up nodes of which demand will be transported to train station
D	Set of all drop-off nodes, $D = \{n+1, n+2, \ldots, 2n\}$
D^t	Set of all drop-off nodes of which demand will be transported from train station
T	Set of the train station, composed of two dummy nodes T_p and T_d
I	Set of all time intervals for pods to enter train station
V	Set of all pods
J	Set of all items
J^i	Set of items set to depart from node i
Γ	Set of all cargo types
Parameters	
u	Maximum platoon length
T_k	Longest travel time per service trip per pod
α_c	The coefficient for total travel cost term in objective function
c_{ij}	Travel distance per pod on arc (i, j)
t_{ij}	Travel time on arc (i, j)
τ_i^k	Pod k's service time at node i
a^i	Expected arrival time at node i
α_p	Unit cost for skipping passenger demands
α_o^p	Unit cost for passenger demands taking detour
α_o^f	Unit cost for freight demands taking detour
α_l^p	Unit cost for pods arriving late at a passenger-related node
α_l^f	Unit cost for pods arriving late at a freight-related node
σ_v	Priority level of item v
α_k	Unit cost for deploying a pod
C_{rs}	Compatibility indicator, 1 if cargo type r and s are compatible, 0 otherwise
w_i	Width of demand at node i
d_i	Depth of demand at node i
h_i	Height of demand at node i
q_i	Weight of demand at node i
W_k	Width limit of pod k
D_k	Depth limit of pod k
H_k	Height limit of pod k
Q_k	Weight capacity of pod k
C^t	Train station capacity
ρ	Average train departure time period
M	Sufficient large positive number
Decision variables	
x_{ij}^k	1 if pod k travels on arc (i, j), 0 otherwise
s_i^p	1 if passenger pick-up node i is skipped, 0 otherwise
o_i^k	Continuous variable denoting the extra time taken for detour
e^i	Early arrival time at node i
l^i	Late arrival time at node i
B_i^k	Vehicle k's arrival time at node i, continuous
Q_i^k	Quotient part of modulo calculation, integer
C_n^k	1 if pod k arrives train station in time interval n, 0 otherwise
y_{ik}	1 if demand at node i is served by pod k, 0 otherwise
v_k	1 if pod k is deployed, 0 otherwise
f_{rk}^v	For item v belongs to cargo type r, $f_{rk}^v = 1$ if it′s assigned to pod k, 0 otherwise
(X_i^k, Y_i^k, Z_i^k)	Coordinate of demand placement pivot point (left-rear-bottom point) at node i in pod k

Appendix B. Model formulation

$$
\begin{aligned}
Min\ Z = \quad & \sum_{i\in N}\sum_{j\in N}\sum_{k\in V}\alpha_c c_{ij} x_{ij}^k + \sum_{i\in P^p} s_i^p * \alpha_p * \sigma_v + \sum_k \alpha_k * v_k \\
& +\alpha_o^p \sum_{i\in P^p}\sum_{k\in V} o_i^k \\
& +\alpha_o^f \sum_{i\in P^f}\sum_{k\in V} o_i^k \\
& +\alpha_l^p \sum_{i\in P^p}\sum_{k\in V} l_i * \omega_i * \sigma_v \\
& +\alpha_l^f \sum_{i\in P^f}\sum_{k\in V} l_i * \omega_i * \sigma_v
\end{aligned}
$$

Subject to:

$$\sum_{k\in V} y_{ik} + s_i^p = 1 \qquad \forall i \in P^p \tag{B.1}$$

$$\sum_{k\in V} y_{ik} = 1 \qquad \forall i \in P^f \tag{B.2}$$

$$X_i^k + w_i * y_{ik} \leq W_k * v_k \qquad \forall i \in P,\ k \in V \tag{B.3}$$

$$Y_i^k + h_i * y_{ik} \leq H_k * v_k \qquad \forall i \in P,\ k \in V \tag{B.4}$$

$$Z_i^k + d_i * y_{ik} \leq D_k * v_k \qquad \forall i \in P,\ k \in V \tag{B.5}$$

$$\sum_{i\in P} q_i^k \leq Q_k * v_k \qquad \forall k \in V \tag{B.6}$$

$$\sum_{i\in P} y_{ik} \leq M * \ f_{rk}^v \qquad \forall r \in \Gamma,\ k \in V,\ v \in J^i \tag{B.7}$$

$$f_{rk}^v + f_{sk}^v \leq 1 \qquad \forall r, s \in \Gamma,\ \ v \in J^i,\ k \in V,\ C_{rs} = 0 \tag{B.8}$$

$$X_i^k + w_i \leq X_j^k + M\left(1 - y_{ik}\right) + M\left(1 - y_{jk}\right) \quad \forall i, j \in P,\ i{\leq}j,\ k \in V \tag{B.9}$$

$$Y_i^k + h_i \leq Y_j^k + M\left(1 - y_{ik}\right) + M\left(1 - y_{jk}\right) \quad \forall i, j \in P,\ i{\leq}j,\ k \in V \tag{B.10}$$

$$Z_i^k + d_i \leq Z_j^k + M\left(1 - y_{ik}\right) + M\left(1 - y_{jk}\right) \quad \forall i, j \in P,\ i{\leq}j,\ k \in V \tag{B.11}$$

$$y_{ik} \leq q_i^k \qquad \forall i \in P,\ k \in V \tag{B.12}$$

$$q_0^k = q_{2n+1}^k = 0 \qquad \forall k \in V \tag{B.13}$$

$$\sum_{j \in N} \sum_{k \in V} x_{ij}^k + s_i^p = 1 \qquad \forall i \in P^p \tag{B.14}$$

$$\sum_{j \in N} \sum_{k \in V} x_{ij}^k = 1 \qquad \forall i \in N/P^p \tag{B.15}$$

$$\sum_{i \in N} \sum_{j \in N} x_{ij}^k \leq M * v_k \qquad \forall k \in V \tag{B.16}$$

$$\sum_{j \in N} x_{ij}^k - \sum_{j \in N} x_{i+n,j}^k = 0 \qquad \forall i \in P/P^t,\ k \in V \tag{B.17}$$

$$\sum_{j \in N} x_{oj}^k \leq v_k \qquad \forall k \in V \tag{B.18}$$

$$\sum_{j \in N} x_{ij}^k - \sum_{j \in N} x_{ji}^k = 0 \qquad \forall i \in P \cup D,\ k \in V \tag{B.19}$$

$$\sum_{i \in N} x_{i,2n+1}^k \leq v_k \qquad \forall k \in V \tag{B.20}$$

$$\sum_{j \in N} x_{0,j}^k = \sum_{i \in N} x_{i,2n+1}^k \qquad \forall k \in V \tag{B.21}$$

$$\sum_{j \in N} x_{i,j}^k - \sum_{j \in N} x_{N^t,j}^k = 0 \qquad \forall i \in P^t,\ k \in V \tag{B.22}$$

$$B_j^k \geq \left(B_i^k + \tau_i^k + t_{ij}\right) - M(1 - x_{ij}^k) \qquad \forall i, j \in N,\ k \in V \tag{B.23}$$

$$B_{i+n}^k \geq (B_i^k + \tau_i^k + t_{i,i+n}) - M(1 - \sum_{j \in N} x_{ij}^k) \qquad \forall i, j \in N,\ k \in V \tag{B.24}$$

$$B_{i+n}^k - (B_i^k + \tau_i^k + t_{i,i+n}) - M(1 - \sum_{j \in N} x_{ij}^k) \leq o_i^k \qquad \forall i \in P/P^t,\ K \in V \tag{B.25}$$

$$B_{T_d}^k - (B_i^k + \tau_i^k + t_{i,T_d}) - M(1 - \sum_{j \in N} x_{ij}^k) \leq o_i^k \qquad \forall i \in P^t,\ K \in V \tag{B.26}$$

$$B_{2n+1}^k - B_0^k \leq T_k \qquad \forall k \in V \tag{B.27}$$

$$B_i^k \geq a_i \qquad \forall i \in P,\ k \in V \tag{B.28}$$

$$B_{t_p}^k \ + M(1 - \sum_{j \in N} x_{ij}^k) \geq a_i \qquad \forall i \in D^t,\ k \in V \tag{B.29}$$

$$B_i^k - a^i - M(1 - \sum_{j \in N} x_{ij}^k) \leq l_i \qquad \forall i \in P,\ k \in V \tag{B.30}$$

$$B_i^k \ = \rho Q_i^k + \rho \qquad \forall i \in T, k \in V \tag{B.31}$$

$$Q_i^k = \sum_{n \in I} n * C_n^k \qquad \forall i \in T,\ k \in V \tag{B.32}$$

$$Q_i^k - n \leq M(1 - C_n^k) \qquad \forall i \in T,\ n \in I, k \in V \tag{B.33}$$

$$Q_i^k - n \geq \ - M(1 - C_n^k) \qquad \forall i \in T,\ n \in I, k \in V \tag{B.34}$$

$$\sum_{k \in V} C_n^k \leq C^t \qquad \forall n \in I \tag{B.35}$$

The objective function consists of seven terms, including the total travel distance cost, penalty cost for not serving passenger transport demand, the fixed cost of deploying pods, the total detour penalties and the tardiness penalties.

(B.1) and (B.2) ensure every demand node i is either served by exactly one pod k or skipped. (B.3)-(B.5) measure the geometrical constraints in another manner, which is, given the pivot coordinate of placement position, the cargo to be loaded at node i should be kept within the box. (B.6) states that the weight of loaded items in pod k should not exceed the weight capacity limit of the pod. (B.7) and (B.8) stated that two items belonging to incompatible cargo categories should not be transported by the same pod. (B.9) and (B.11) are the non-overlapping constraints, restricting two items (v and w) which are transported by the same pod k cannot overlap one another on every projection plane (xOy, yOz, xOz). At least one of these three constraints should be valid to fulfill the non-overlapping requirement. (B.12) restricts the relationship between q_i^k and y_{ik}. When demand at node i is set to be transported by pod k, q_i^k should be greater than 0, otherwise there are no demands depart from node i and q_i^k should be 0. (B.13) defines that the load of each pod at both start and end depot should be 0.

(B.14) and (B.15) ensure each customer node is visited exactly once by one pod, or the node could be skipped if it's a passenger pick-up node. (B.16) makes sure only if a pod is deployed could it travel in the network. (B.17) restrained every demand request that won't be transported to the train station will ultimately arrive at its destination. (B.18) and (B.20) set up limitations on the departure node and destination node of each pod, (B.21) ensures the number of pods departing from the starting node is the same as the number of pods entering the destination node. (B.19) is the flow conservation constraint for each node in the network, it refers to each pod that should arrive at each non-depot node and then leave the node, to ensure the continuity of service trips. (B.22) sets a specific routing constraint for train stations. It is assumed that the train station node can be visited by multiple pods.

(B.23)-(B.30) are the time-related constraints. A sketch demonstrates the timeline of this system is as following Figure B.18

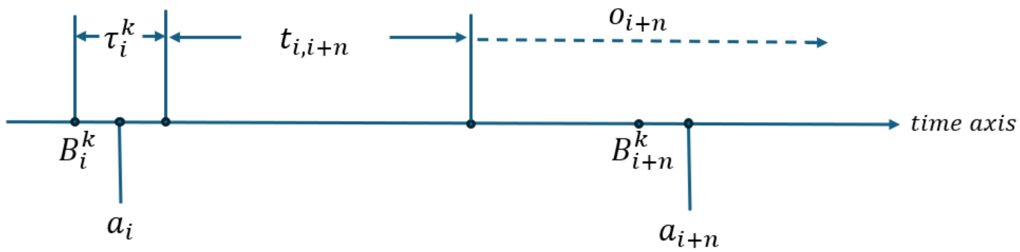

Figure B.18: Timeline

(B.23) denotes that the arrival time of pod k at the following node j should be no earlier than the sum of arrival time and service time at node i and the travel time on arc (i, j) if pod k travels on arc (i, j), this constraint ensures temporal continuity between each two consecutive segments in a service trip. (B.24) ensures each delivery request's arrival time at its destination node should be no earlier than the sum of the arrival time of pod k at pick-up node i, service time at node i and travel time between pick-up node i and its corresponding drop-off node $i + n$. (B.25) allows the detour which takes place during the transport services, the consequence of introducing the detour will also be included in the objective function. (B.26) is similar to (B.25), the only difference between them is the pick-up node-set.

(B.27) bounds the upper limit for pod k finishing a single service trip. (B.28) and (B.29) forbids any pod k arrive earlier than expected arrival time at node i. Constraint (B.30) calculates the delay of pod k when arriving at node i, this term l_i will be returned to the objective function to calculate the tardiness penalty.

The following constraints are correlated with the train station capacity, and are proposed together with a fellow student [44]. For the sake of simplicity, we hereby assume the time intervals (denoted as ρ) are uniform, for example, 10 minutes. A diagram demonstrating the timeline of the train station approaching is as follows:

(B.31) introduces a new variable Q_i^k denotes the number of intervals the arrival time of pod k arrives at train station i. To give an example, if a pod arrives at the train station at 22^{nd} minute, then the pod arrives during the third time interval, thus Q_i^k equals to 2. (B.32)-(B.34) is a set of constraints help to set correct C_n^k to 1 when $Q_{T_p}^k$ is not zero, which means, the number n should be corresponding to the n in variable C_n^k. Lastly, (B.35) secures the initial target of this constraint set: limiting the inflow to the train station not exceeding train station capacity C^t.

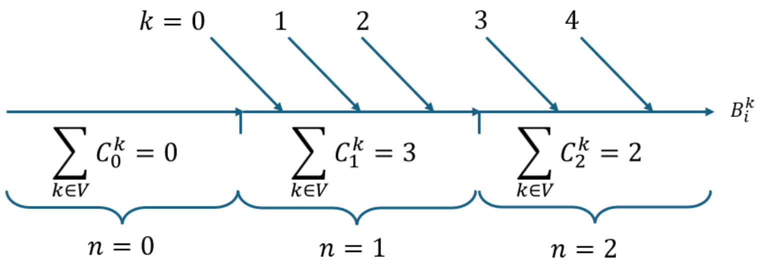

Figure B.19: Timeline - Train station capacity

Table C.1: Cargo compatibility matrix

Category	1	2	3	4
1	0	0	1	1
2	0	0	0	0
3	1	0	0	0
4	1	0	0	0

Appendix C. Compatibility matrix

Appendix D. Parameter tables

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Table D.2: Parameter values used in the sensitivity analysis

Symbol	Description	Value	Unit
Train station characteristics			
C^t	Max. throughput of the train station per period	5	Pods
ρ	Minutes of one time interval	5	minutes
Pods characteristics			
W	Width of pods' interior space	2.4	meters
H	Height of pods' interior space	2.5	meters
D	Depth (Length) of pods' interior space	6	meters
$Weight$	Maximum weight of freights a pod can load	850	kg
v_{pod}	Average travel speed of pods	10	km/h
Penalty costs			
α_p	Demand skipping penalty	20	per node
α_k	Penalty for using a pod	20	per pod
α_c	Travel distance penalty	2.5	per km
α_l^f	Tardiness penalty for freight	2	per min
α_l^p	Tardiness penalty for passenger	2	per min
α_o^f	Detour penalty for freight	0.15	per min
α_o^p	Detour penalty for passenger	0.1	per min
Other			
n_P	Number of pickup nodes in set P^-	4	nodes
n_N	Number of pickup and delivery nodes combined	10	nodes
n_E	Total number of intervals	10	intervals
M	Big-M value	1500	-

Table D.4: Parameter values used for sensitivity analysis on the available number of pods

Symbol	Description	Value	Unit
Penalty costs			
α_p	Demand skipping penalty	20	per node
α_k	Penalty for using a pod	2	per pod
α_c	Travel distance penalty	0.5	per km
α_l^f	Tardiness penalty for freight	2	per min
α_l^p	Tardiness penalty for passenger	2	per min
α_o^f	Detour penalty for freight	0.15	per min
α_o^p	Detour penalty for passenger	0.1	per min

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